An empirical study on causes and consequences of inflation and inflation uncertainty

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Diplom-Volkswirt Matthias Hartmann, M.Sc.
aus Deggendorf

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Dekan:
Prof. Dr. Roman Liesenfeld

Erstberichterstattender:
Prof. Dr. Helmut Herwartz

Zweitberichterstattender:
Prof. Dr.Stefan Reitz

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Vorwort

Die vorliegende Arbeit ist entstanden, während ich als wissenschaftlicher Mitarbeiter am Institut für Statistik und Ökonometrie der Christian-Albrechts-Universität zu Kiel tätig war. Mein besonderer Dank gilt meinem Doktorvater Professor Dr. Helmut Herwartz. Seine umsichtige Anleitung und hervorragende Betreuung haben entscheidend zum Gelingen dieser Arbeit beigetragen. Herrn Professor Dr. Stefan Reitz danke ich herzlich für seine Tätigkeit als Zweitgutachter. Darüber hinaus danke ich Herrn Professor Dr. Roman Liesenfeld und Professor Dr. Uwe Jensen für vielfältige fachliche Anregungen und Hilfestellungen.

Die Kapitel 5-8 dieser Dissertation basieren auf Arbeiten, die in Kooperation mit Herrn Professor Dr. Helmut Herwartz entstanden sind. Kapitel 4 basiert auf einer Zusammenarbeit mit Herrn Dr. Jan Roestel. Herr Diplom-Volkswirt Steffen Ahrens war an der Studie, die Kapitel 9 zugrunde liegt, maßgeblich beteiligt. Derjenige Anteil von Kapitel 8, der sich mit der bei *Macroeconomic Dynamics* eingereichten Studie "Did the introduction of the Euro impact on inflation uncertainty? - An empirical assessment" überschneidet, wird mit Genehmigung von Cambridge University Press veröffentlicht.

Für vielfältige fachliche Diskussionen und das anregende und angenehme Arbeitsumfeld danke ich Herrn Diplom-Volkswirt Steffen Ahrens, Herrn Diplom-Volkswirt Bastian Gribisch, Herrn Diplom-Volkswirt Marcus Pawel, Herrn Diplom-Volkswirt Malte Rengel, Herrn Dr. Jan Roestel und Herrn Yabibal Walle, M.Sc.

Ohne die Ermutigung und Unterstützung meiner Familie wäre weder mein Studium noch die Fertigstellung dieser Arbeit möglich gewesen.

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1. INTRODUCTION

1.1 Motivation

The current economic crisis commands nonconventional steps in monetary and fiscal policy. Recent years have witnessed large-scale stimulus packages from monetary and fiscal authorities and increasing levels of government debt. Monetary authorities are increasingly under pressure to reduce government debt by raising inflation targets (Aizenman and Marion 2011). The coincidence of near-zero nominal interest rates in the US, trade imbalances in the European Monetary Union (EMU) and the increasing level of sovereign debt across western economies have raised considerable disagreement on the obligations of monetary policy. Central banks traditionally emphasise the merits of their credibility to keep inflation low and stable. On the other hand, there is hope that higher (expected) inflation might resolve the limits of conventional monetary policy at the zero lower bound, mitigate current account imbalances in the EMU and reduce the problem of unsustainable government debt (Eggertsson and Woodford 2003; Krugman 1998; Davig et al. 2011). This provokes concerns about welfare losses from excess inflation among customers, firms and investors alike.

The aim of this thesis is to evaluate potential causes and effects of inflation and its associated uncertainty. Particular emphasis is put on the discussion of alternative means to measure the latent inflation uncertainty (IU henceforth). The importance of IU is reflected in the specification of several well-known macroeconomic models which include inflation expectations as one of their crucial components. Examples are the Fisher relation (Fisher 1930) or several recitations of the Phillips curve (Clarida et al. 1999; Friedman 1968; Phelps 1968). Moreover, inflation expectations might affect consumption smoothing (Hördahl 2008) or firms' investment and price setting (Levi and Makin 1979; Taylor 2000). Deviations of expectations from realised inflation are usually costly for the decision taker. Hence, the more crucial the role of inflation expectations is, the more meaningful it is to explicitly consider the uncertainty about future inflation.

The related literature describes various influences of IU. Chapter 3 highlights some of the most prominent assertions. For the most part, the signs and directions of causal relations are controversial. This has triggered the examination of causes and consequences of IU in a large and rapidly evolving empirical literature. However, since IU is an unobservable quantity, empirical investigations have to determine a suitable way to measure IU. Considerable parts of the empirical literature approximate IU by means of (generalised) autoregressive conditional heteroscedasticity (GARCH) models (Bollerslev 1986; Engle 1982). In the GARCH methodology, IU is quantified from an ex-post point of view. This is particularly well-suited for the identification of historically remarkable periods like hyperinflation or financial turmoil. An alternative means to measure IU is to employ surveys of experts' ex-ante inflation predictions. Theoretical concepts of IU primarily refer to risks of welfare losses from future inflation (Ball and Cecchetti 1990). Presuming that monetary authorities, consumers and investors act upon perceived risks arising from prospective inflation, obtaining IU measures by means of out-of-sample (OS) methods seems to be recommendable for the support of economic decision taking. For the same reason, we argue that GARCH-based inference on (Granger-) causal relations should be complemented with corresponding OS tests. Thus, we apply out-of-sample methods also to draw inference on causal relations.

A further important feature of this work is that causal inference is throughout based on sizeable cross sections of data. The largest cross section we consider comprises 34 developed and emerging economies. The incorporation of large cross sections for causal inference and the evaluation of IU measures is rarely encountered in the related literature. By drawing inference from the cross-sectional variation of economy-specific estimates, we are able to put the (partially) ambiguous findings from previous single-economy studies into context. We examine several potential determinants of cross-economy heterogeneity. For example, economies might differ with regard to their respective historical inflation experiences. Moreover, the formation of a currency union is accompanied by changes in the systemic framework of monetary policy (Feldstein 2005; Mundell 1961; Wickens 2010). Apart from a direct influence on inflation or IU, such conditions are often described as a crucial factor which affects the nature of respective causal relations (Cukierman and Meltzer 1986).

For this reason, we examine the influence of the systemic conditions of monetary policy on IU. In particular, we assess the institutional impact of participation in the EMU in the framework of both the aforementioned GARCH approach and also by means of forecasting-based IU measures. We argue that to evaluate the impact of systemic conditions of monetary policy, the comparison between economies inside and outside the currency union is crucial. This is a further reason to rely on a multitude of economies. Moreover, we evaluate the potential dependence of the Phillips curve relation (PC, Phillips 1958) on inflation and IU. It is frequently asserted that these factors might influence both aggregate price setting and the relation between inflation rates and business cycle dynamics. A semiparametric representation of the New Keynesian Phillips curve (NKPC) serves as a means to assess whether these relations are systematically varying as functions of inflation or IU. This allows to assess the effects of both variables on a causal relation in a quantitative way. Therefore we complement the analysis from earlier chapters where mostly discrete influences like EMU participation and nonparticipation or higher and lower average inflation rates are considered as potential state variables.

1.2 Chapter overview

The remaining part of the thesis has the following structure. In chapter 2, we describe the data sets employed in the distinct chapters of the thesis. Some statistical properties of the time series are described. Next, a summary of the related literature is given in chapter 3.

In chapter 4, we estimate uncertainty and test for causal relations by means of a GARCH approach. The employed model is largely similar to specifications which are typically considered in studies on aggregate uncertainty. This allows to relate our findings to those from previous investigations. The empirical analysis is confined to the current era of low inflation policies. A focus on more recent data contains the risk of smoothing over distinct regimes in the inflation and IU process. We also investigate if conditioning on particular circumstances affects inferential conclusions.

In chapter 5, we introduce a set of alternative forecasting-based IU measures. The IU quantifications mimic commonly applied methods of IU approximation such as time-series methods in the GARCH tradition or dispersion-of-opinions measures as usually derived from expectation surveys. The hypotheses assessed in chapter 4 are reexamined by means of these alternative IU metrics in subsequent chapters.

The advantages and disadvantages of distinct choices to quantify IU are discussed in chapter 6. An out-of-sample forecast comparison highlights the merits of alternative IU measures as predictor variables of long-term interest rates. The findings from the comparative assessment of IU measures guide the choice of the set of measures in subsequent investigations.

In chapter 7, we examine the bilateral dependence between inflation and IU. This completes the examination from chapter 4, where the impact of inflation on IU is not investigated. The relation is analysed by means of both IS tests and OS forecasting comparisons.

In chapter 8, the influence of the systemic conditions on the overall level of IU is discussed. We examine whether participation in the EMU has lead to significant benefits for its member states in terms of reduced IU. We compare the level of IU in EMU members and in economies which did not adopt the Euro. This approximates a counterfactual situation which corresponds to the absence of a common currency.

In chapter 9, the dependence of the Phillips curve (PC) relation on influences like the inflation rate and IU is investigated. A semiparametric representation of the NKPC serves as the estimation framework to test for state-dependence. In extant empirical studies, the problem of residual heteroscedasticity is widely regarded as a major deterrence to draw meaningful inference on the factor-dependence of the NKPC (Cogley and Sbordone 2005; Fernandez-Villaverde et al. 2007). We cope with this problem by means of a factor-based bootstrap approach recently proposed by Herwartz and Xu (2009, 2010). Finally, chapter 10 concludes.

2. DATA

In the following, the distinct data sets that are employed in subsequent chapters are introduced. We also comment briefly on some properties of the data series.

2.1 *Five cross sectional data sets*

The first collection of series covers the time period between 1990M1 and 2010M1. The data set includes the consumer price index (CPI_t) and the index of industrial production (IP_t). The cross section comprises $i = 1, ..., 34$ economies and is referred to as $\mathcal{M}34$. The data set additionally incorporates growth rates of the oil price (oil_t), which are obtained for West Texas Intermediate crude oil in terms of the respective economies' domestic currencies. The names of particular economies are listed in table 2.1. The second cross section is a subset of $\mathcal{M}34$. It comprises monthly observations for the period 1988M1 to 2011M5 and 18 economies, namely Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK and the US. This data set is referred to as $\mathcal{M}18$ and includes the Dow Jones Industrials Average Index (dow_t) and foreign exchange rates with respect to the US dollar (FX_t) in addition. These series for the same group of economies at the quarterly frequency is termed the $\mathcal{Q}18$ data set, which additionally incorporates annual constant maturity yields on government bonds with a contract length of about 10 years (R_t). The $\mathcal{Q}18$ data covers the period between 1988Q1 and 2011Q1. The $\mathcal{M}22$ data comprises monthly data and includes Greece, Israel, Korea and Taiwan as members of the cross section in addition to the economies in $\mathcal{M}18$. Finally, the $\mathcal{Q}14$ data set entails quarterly real GDP series and annual inflation from 1961Q4 to 2011Q1. The list of economies in this data set is Australia, Belgium, Canada, Spain, Finland, France, Italy, Japan, the Netherlands, New Zealand, Portugal, Sweden, the UK and the US. Whereas in chapter 4, annual inflation rates and output growth rates obtain as $\pi_t = 1200 \times \ln(CPI_t/CPI_{t-1})$ and $y_t = 1200 \times \ln(IP_t/IP_{t-1})$, respectively, these quantities are for all other data sets at the monthly frequency defined as $\pi_t = \ln(CPI_t/CPI_{t-12})$ and $y_t = \ln(IP_t/IP_{t-12})$, respectively. For the $\mathcal{Q}18$ data set, $\pi_t = \ln(CPI_t/CPI_{t-4})$ and $y_t = \ln(IP_t/IP_{t-4})$. In chapter 9, where the $\mathcal{Q}14$ data set is employed, annual inflation is measured by means of the GDP deflator (DEF_t) and $\pi_t = 400 \times \ln(DEF_t/DEF_{t-1})$. We consider these alternative definitions and series to facilitate the comparability of respective results to those obtained in the related literature on GARCH models and the structural New Keynesian Phillips curve (Bredin and Fountas 2009; Galí and Gertler 1999). In general, employing annual price differences like $\pi_t = \ln(CPI_t/CPI_{t-12})$ and $y_t = \ln(IP_t/IP_{t-12})$ to measure inflation and output growth might be advantageous since this obtains data series with less complicated patterns of serial dependence. This facilitates the modelling of inflation and IU by means of parsimonious dynamic specifications[1]. Additionally, $\mathcal{Q}14$ includes the so-called labour share (of aggregate income), denoted mc_t, which corresponds to unit labour costs in real terms. With ulc_t and p_t denoting the logarithm of unit labour costs and the GDP deflator, respectively, we obtain $mc_t = ulc_t - p_t$.

[1] Diagnostic tests on the serial correlation characteristics of disturbances from distinct inflation models which document these properties are available from the author upon request.

From the industrial output and GDP data, we obtain estimates of the output gap, denoted $\tilde{y}_t = y_t - \bar{y}_t^{HP}$, which are employed in all chapters[2]. These estimates are calculated by means of the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997) with smoothing parameter 129600 (Ravn and Uhlig 2002) for the data sets at the monthly frequency and with the respective parameter set to 1600 for quarterly data. In those cases where $\tilde{y}_t$ enters a forecasting model, trend estimates $\bar{y}_t^{HP}$ are computed at each prediction step conditional on available data which is used to form the current prediction. Thereby we generate out-of-sample inflation forecasts in the most realistic way. Preliminary predictions of y_t are obtained to alleviate the weak precision of HP trend estimates at the end of the estimation window.

All series are seasonally adjusted and obtained from Datastream in case of $\mathcal{M}34$, $\mathcal{M}22$, $\mathcal{M}18$ and $\mathcal{Q}18$, whereas the data source is the OECD Economic Outlook in case of $\mathcal{Q}14$.

2.2 Time series properties

In table 2.1, the integration properties of the inflation series in the $\mathcal{M}34$ data set are reported. Since $\mathcal{M}34$ covers the majority of economies considered in the other data sets, these series are regarded as representative. Throughout, we let T_0^* and T^* denote the initial and the final observation in the respective sample period, where "$*$" indicates that T_0^* and T^* may refer to distinct dates in the respective data sets. Evidence on integration is obtained by means of heteroscedasticity consistent ADF unit root tests (Cavaliere and Taylor 2008). The ADF regressions include an intercept term. Lag order selection is carried out by means of the Schwartz information criterion (SIC). If country specific steady state inflation does not substantially change over the considered

[2] In chapter 7, an alternative output gap estimate $\tilde{y}_t^{CF} = y_t - \bar{y}_t^{CF}$ is based on the band pass filter with boundary coefficients $b_l, b_u = \{2, 24\}$ as recommended for monthly data (Christiano and Fitzgerald 2003).

sampling period one would expect inflation rates to be stationary. The ADF diagnostics suggest that only in 6 out of 34 countries, inflation rates are nonstationary. These economies are Argentina, Brazil, Columbia, Hungary, Peru and Poland. In these economies, inflation levels have been rather high during recent decades. The reduction of inflation rates might still be at an earlier stage in these cases as compared to the rest of the cross section. Furthermore, ADF statistics for output growth rates, indicating stationarity for all economies. Corresponding statistics are not listed explicitly. The evidence on stationary inflation rates likely reflects that most of the countries have successfully pursued low-inflation policies during recent decades. Table 2.1 further shows multivariate ARCH-LM test diagnostics (cf. Engle 1982; Lütkepohl 2005) for the inflation series in $\mathcal{M}34$. In the test regression, a lag order of 3 is considered. The series are prefiltered by means of a vector autoregressive model described in equation (4.2). The presence of multivariate ARCH effects justifies distinct ways to model conditional second moments dynamics in subsequent chapters. The diagnostics indicate significant ARCH effects in the nonstandardized model innovations for the majority of economies[3].

[3] Qualitatively similar results are also obtained for the other data sets. In particular, we find significant ARCH effects also for alternative definitions of inflation and for the quarterly data series. These results are reported in chapter 9. Moreover, ARCH dynamics have been documented for quarterly inflation data in widely cited contributions of Engle (1982) or Bollerslev (1986).

Table 2.1: Unit root- and multivariate ARCH test diagnostics

	ADF^{π}	LM		ADF^{π}	LM		ADF^{π}	LM
Argentina (AG)	−7.636	144.683	Hungary (HN)	−1.85	103.713	Norway (NW)	−11.73	60.530
	(0.49)	(0.00)		(0.61)	(0.00)		(0.00)	(0.00)
Austria (AT)	−13.78	80.653	India (IN)	−3.73	49.413	Portugal(PT)	−3.15	44.574
	(0.00)	(0.00)		(0.01)	(0.01)		(0.03)	(0.02)
Barbados (BB)	−14.16	101.970	Ireland (IR)	−3.88	35.151	Peru (PE)	−5.164	100.670
	(0.00)	(0.00)		(0.00)	(0.14)		(0.99)	(0.00)
Belgium (BG)	−13.19	22.303	Israel (IS)	−6.45	98.350	Poland (PO)	−4.456	97.411
	(0.00)	(0.72)		(0.00)	(0.00)		(0.12)	(0.00)
Brazil (BR)	−5.77	77.564	Italy (IT)	−4.03	38.398	Spain (ES)	−9.77	68.606
	(0.45)	(0.00)		(0.00)	(0.07)		(0.00)	(0.00)
Canada (CA)	−6.03	81.477	Jordan (JO)	−8.35	62.969	Sweden (SD)	−8.10	77.826
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
Columbia (CO)	−1.32	53.917	Japan (JP)	−13.80	99.320	Turkey (TK)	−7.115	49.511
	(0.69)	(0.00)		(0.00)	(0.00)		(0.00)	(0.01)
Denmark (DK)	−15.88	48.837	Korea (KO)	−10.17	180.340	Taiwan(TW)	−19.23	129.675
	(0.00)	(0.01)		(0.00)	(0.00)		(0.00)	(0.00)
Finland (FN)	−5.17	52.996	Luxembourg (LU)	−16.99	92.869	UK	−5.88	210.513
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
France (FR)	−13.66	21.976	Mexico(MX)	−3.94	133.319	US	−10.18	193.921
	(0.00)	(0.74)		(0.02)	(0.00)		(0.00)	(0.00)
Germany (DE)	−6.50	52.890	Malaysia (MY)	−11.78	23.498			
	(0.00)	(0.00)		(0.00)	(0.66)			
Greece (GR)	−3.62	56.790	Netherlands (NL)	−16.16	47.790			
	(0.04)	(0.00)		(0.00)	(0.01)			

3. LITERATURE REVIEW

In this chapter, we review particularly relevant parts of the theoretical and empirical literature on monetary policy and IU. After an overview of distinct means to measure IU, the most important studies on the determinants of inflation and IU are summarised. A review of hypotheses and empirical findings on potential consequences of both quantities follows.

3.1 The measurement of inflation uncertainty

Given the multitude of opposite theories on the impact of IU, its economic meaning is often discussed from an empirical perspective. However, inflation uncertainty is unobservable. Hence, a suitable way to approximate the latent uncertainty process has to be determined. In earlier contributions, IU is measured by means of standard deviations of inflation within rolling sample windows (Fama 1976). Such methods have been critisised not to measure uncertainty, but mere volatility. A distinction between the two is important since inflation volatility might be at least partly predictable. In examinations by Engle (1982), Bollerslev (1986) or Zarnowitz and Lambros (1987) two principal approaches of IU measurement are introduced (Giordani and Söderlind 2003). Whereas the former studies initiated the IU quantification by means of the (G)ARCH methodology, Zarnowitz and Lambros (1987) describe how uncertainty may be expressed by means of experts' forecast surveys. Most subsequent studies on IU measurement or causal analysis are based upon one of these approaches. The former approach draws explanatory content from historical observations. The latter methods emphasise the heterogeneity of inflation expectations. Apart from relying on distinct sources of information, the two methods also process information in different ways (Batchelor and Dua 1996, Mankiw and Reis 2004). A speciality of the GARCH approach is that uncertainty measurement and causal inference are carried out in the same model framework. While this is appealing in terms of exposition, it can lead to spurious conclusions. This is particularly harmful if the evidence for contrary hypotheses like the FB and CM hypotheses is compared. Ma et al. (2007) show that cases of less pronounced or absent conditional heteroscedasticity may lead to overrejection of significance tests for the GARCH parameter in the GARCH(1,1) model. Furthermore, Lundblad (2007) documents that small-sample biases in GARCH-in-mean models (Engle et al. 1987) can give rise to insignificant estimates of the impact of uncertainty on the conditional mean process. Moreover, it is well documented that inflation and IU processes are characterised by considerable structural change (Evans and Wachtel 1993). For example, empirical studies relying on models from the GARCH family often consider data sets which gather observations from the Bretton Woods era and episodes of high inflation with later periods characterised by the widespread adoption of inflation targeting. Difficulties associated with specifying the timing of such regime changes might result in largely biased estimates and predictions. Therefore, estimates based on long historical spans of data may not be a reliable guidance for economic policy and investment. In particular, significant results from historical samples might give rise to problems like overconfidence or "hindsight bias" in economic decision-taking (Guidolin and Timmermann 2005).

3.2 Determinants of inflation and IU

The Phillips curve is the most prominent theoretical model of inflation dynamics. It relates the inflation rate to some measure of real activity. The New Keynesian representation of the Phillips curve (NKPC) is investigated by Galí and Gertler (1999), Sbordone (2005) or Rudd and Whelan (2005). However, many empirical investigations on the NKPC have documented theoretically implausible coefficient estimates. Moreover, estimates are reported to differ largely with respect to the considered sample period or cross section (Abbas and Sgro 2011; Guay et al. 2002; Jondeau and Bihan 2005; Kuttner and Robinson 2012). Ambiguous findings from distinct representations of the PC are a well-documented stylised fact since several decades (Lucas and Sargent 1979). Rudd and Whelan (2005) conject that one reason for such inadequacies might be an unsuitable choice of the business cycle measure. Moreover, the relation between inflation and real activity might depend on certain observable factors or systemic conditions (Ball et al. 1988; Caporale and Kontonikas 2009; Danziger 1983).

Inflation, in turn, is in theory described as an important factor which might give rise to IU. Friedman (1977) states that IU may emerge as a result of excess inflation. This assertion has been formalised by Ball (1992). In many subsequent studies, this effect is referred to as the Friedman-Ball (FB) hypothesis (Fountas 2001; Grier and Perry 1998). Empirical studies on this assertion include Engle (1982), Baillie et al. (1996) or Daal et al. (2005). These studies, however, disagree with respect to the prevalence and the sign of the examined causal relations.

Moreover, the institutional setting in which monetary policy is conducted is often described as an important determinant of inflation and IU. The influence of institutions like monetary authorities is particularly apparent if economies participate in a currency union. There are opposite theories on which institutional background may provide the most favourable insurance against upcoming inflation risks. In particular, it is controversial if the formation of a monetary union is a sensible way to protect its member states from excess IU. Mundell (1961), Alesina and Barro (2002) and Alesina et al. (2003) discuss these issues when characterising optimal currency areas. They argue that members of a monetary union benefit from a central bank with a reputation to successfully stabilise inflation. Similarly, Cukierman (2000) argues that the nonsynchronous timing of elections in member states increases the freedom of monetary policy to focus on the containment of inflation dynamics. In contrast, the formation of a monetary union might also increase overall IU. This might result, for example, as a matter of disparities in the economic conditions of participating states. Feldstein (2005) points out that the formation of a monetary union generates a free-rider problem if member countries retain their fiscal authority. In such cases, large budget deficits among member states may put the central bank under pressure to allow for higher inflation rates. Resulting disadvantages have to be born by all economies in the union. As argued by Davig et al. (2011), inflation risks arise in such situations as it is unclear to which extent such pressures can be repelled. In addition, threats to IU may result from persistent inflation differentials among member states (ECB 2003). Such differences cannot be accommodated by a single monetary policy and potentially increase overall IU. It is often unclear how far prospects of rising inflation have to spread over member economies in order to be considered by the central bank (Arnold and Lemmen 2008). Caporale and Kontonikas (2009) and Caporale et al. (2011) investigate the influence of currency union participation on inflation and IU. Results indicate adverse effects of joining the union for distinct member states of the EMU. Conrad and Karanasos (2005) document a uniform impact of inflation on IU for the UK and the member economies of the EMU, whereas the opposite causal influence is found to depend on the economy-specific characteristics of monetary policy.

The first column of table 3.1 lists some of the most important causal relations. In the second column of the table, some widely cited references are stated. In column 3 we state the empirical model from which inferential conclusions are drawn in subsequent chapters.

Table 3.1: Hypotheses to be examined in the following chapters

Hypothesis			Reference	Empirical model
π	$\leftrightarrow$	y	Phillips (1958)	(4.2), (9.1), (9.3)
IU	$\rightarrow$	y	Friedman (1977)	(4.2)
IU	$\rightarrow$	π	CM, Devereux (1989)	(4.2), (7.1)
IU	$\rightarrow$	R	Levi & Makin (1979)	(6.1)
OU	$\leftrightarrow$	IU	Taylor (1994)	(4.1)
π	$\rightarrow$	IU	FB	(7.1)
π	$\rightarrow$	α	BMR	(9.3)
IU	$\rightarrow$	α	BMR, Danziger (1983)	(9.3)
EMU	$\rightarrow$	IU	Cukierman (2000), Feldstein (2005)	(8.2)

In column 1, α denotes the so-called Calvo (1983) parameter, which is a crucial component of the NKPC. This coefficient is inversely related to the frequency of aggregate price adjustment. The abbreviations CM, FB and BMR in column 2 refer to the assertions of Cukierman and Meltzer hypothesis (1986), Friedman (1977) and Ball (1992) and Ball, Mankiw and Romer (1988), respectively.

3.3 Consequences of inflation and IU

In discussions about the advantages and disadvantages of inflation, the effects of IU are often implicitly ascribed to inflation. Fischer and Modigliani (1978) discuss several potential disadvantages arising from either inflation or IU. They explicitly distinguish between the idiosyncratic effects of the two quantities. The impact of IU on output growth is one of those relations which have attracted particularly strong attention in the theoretical and empirical literature. Friedman (1977) describes how IU reduces output growth as a result of uncertainty about real returns of firms' investment projects. On the other hand, positive output effects of IU are described by Dotsey and Sarte (2000). In their model, IU leads to increases in investment through precautionary savings. A description of the effect of IU on output growth which is related to the Friedman (1977) conjecture is that IU might have a negative influence on interest rates (Blejer and Eden 1979). This effect emerges as a result of firms' reduced credit demand under uncertainty. Conversely, higher IU might also be reflected in higher interest rates, as asserted by Barnea et al. (1979) and Brenner and Landskroner (1983). Such a positive effect might arise due to investors' demand for an inflation risk premium. Moreover, it is often assumed that central bank credibility is beneficial to output growth (Backus and Drifill 1985). Credible monetary authorities, in turn, are typically associated with low levels of IU (Giordani and Söderlind 2003). The impact of IU might also cause variation in the level of inflation itself. In contrast to Friedman (1977) and Ball (1992), Cukierman and Meltzer (CM, 1986) and Devereux (1989) assert that IU might impact on the inflation rate.

Holland (1993), Fountas et al. (2002) and Fountas and Karanasos (2007) empirically investigate the impact of IU on output growth. The FB assertion is investigated by Daal et al. (2005) or Fountas (2001), among others. Moreover, Grier and Perry (2000) or Fountas and Karanasos (2007) examine the relation between IU and the inflation rate as described in CM hypotheses. The effect of IU on interest rates is empirically documented by Buraschi and Jiltsov (2005), Höhrdahl et al. (2006), Lahiri et al. (1988) or Levi and Makin (1979).

In addition to their potential influence on observable quantities, inflation or IU may also affect other causal relations. Many assertions regarding causality are formulated in a way that suggests that the relations might be state-dependent. For example, in the models of Cukierman and Meltzer (1986) or Devereux (1989), IU has to exceed a certain level such that an impact on inflation emerges. Gillman et al. (2004) formalize a model where negative effects of inflation on output growth are more severe in a low inflation environment than for higher inflation rates. Fuhrer (1997) and Taylor (1994) assert that the relation between IU and uncertainty about output growth (OU) might depend on the level of inflation. In particular, Fuhrer (1997) points out that a tradeoff between IU and OU is particularly relevant for low-inflation economies. Gylfason and Herbertsson (2001) postulate that in low inflation countries, growth is more sensitive to inflation changes than in high inflation countries.

Further influences of inflation or IU are discussed in the literature on price adjustment. Widely cited theoretical models of price setting might either be categorised as time-dependent schemes like in Calvo (1983) or Taylor (1999) or as state-dependent (Ball et al. 1988; Caplin and Spulber 1987; Sheshinski and Weiss 1977). In most of the former models, it is assumed that a constant fraction of firms adjusts prices at each time instance. An example for the latter type of adjustment schemes is the model of Danziger (1983), where it is suggested that price setting decisions might be associated with the inflation rate or IU. The NKPC is derived from the Calvo (1983) price adjustment model. In this specification, one particular coefficient, commonly called the Calvo parameter, is assumed to determine the aggregate frequency of price adjustment.

The modelling of nominal rigidities, which is a crucial part of the New Keynesian paradigm by means of the Calvo (1983) model is typically found to be overly restrictive (Ball and Mazumder 2011; Canova 2005; Fernandez-Villaverde et al. 2007). Ball et al. (1988) argue that the level and the volatility of inflation positively affect the adjustment frequency since higher and more uncertain inflation reduce the degree of nominal rigidity. Since the NKPC is based on the Calvo (1983) scheme, empirical comparisons of alternative pricing models might be carried out as tests of parameter constancy in the NKPC model framework. However, if prices are considered to be more flexible at higher inflation rates or IU, this is likely reflected in the conditional volatility of inflation (Sims 2001). Thus, inferential conclusions based on specification tests might be affected by heteroscedasticity in the model disturbances of the NKPC (Cogley and Sargent 2005; Fernandez-Villaverde et al. 2007).

3.4 Summary

Apart from a controversial discussion on the determinants and implications of inflation and IU, the empirical literature provides mixed evidence on the direction and signs of causal relations (Bredin and Fountas 2009; Daal et al. 2005; Lahiri et al. 1988; Rudd and Whelan 2007). Potential reasons for opposite findings might be either that mostly distinct data sets or varying model frameworks are employed to measure uncertainty and test for causal relations (Hartmann and Roestel 2012). As it is argued in Hartmann and Herwartz (2012), unmodelled or misspecified structural change is another reason which might explain the variation of empirical results. Finally, decisions like the participation in a currency union like the EMU are a potential reason for adverse findings. Empirical studies which focus on single EMU member- or non-member economies might arrive at divergent conclusions due to distinct institutional settings (Hartmann and Herwartz 2009). We will address each of these issues in the examinations of causal hypotheses and uncertainty measurement in subsequent chapters.

4. THE TRADITIONAL VIEW - A GARCH MODEL FOR UNCERTAINTY MEASUREMENT AND CAUSAL INFERENCE

4.1 Outline

In this chapter, we investigate the linkages among inflation, inflation uncertainty (IU), output growth and output uncertainty (OU) that typically arise in modern-world economies with low to moderate inflation rates. Existing empirical and theoretical studies disagree with regard to the influence of uncertainty on the joint determination of inflation and output. Empirical models which explicitly acknowledge uncertainty typically require a plentitude of time series observations (40-50 years of monthly data, say). Hence it is not surprising that findings strongly disagree across time and countries. During the past two decades, however, the hegemony of inflation targeting strategies has led a large share of central banks to conduct monetary policy in a similar way (Greenspan 2004). During this time, idiosyncratic characteristics of Granger causalities among inflation, output and respective uncertainties should have been reduced across economies around the world. Therefore, evidence on the overall (i.e. multi economy) relevance of particular causalities is more likely to be decisive if the focus of the investigation centers on this time period.

We intend to empirically identify common features in the interaction among inflation, output growth and respective uncertainties across a large range of distinct economies and the recent policy era. Arguing that empirical investigations on the prevalence of particular linkages might be conducted as tests on whether these exist reliably across distinct types of economies, we estimate uniform bivariate VARX-MGARCH-in-mean models (GARCH-M for short) for 34 industrialized and emerging economies. Individual estimates are aggregated across economies by employing the so-called mean-group (MG) estimator (Pesaran and Smith 1995). Inference on the cross country significance of causal effects is based on the cross-sectional variation in respective economy-specific estimates. Such a framework helps to reduce a number of influences that might have induced empirical disagreement in extant research: On the one hand, cross sectional inference on general transmission dynamics does not require the use of overly 'historical' data sets at the country specific level. Hence, issues of structural change or cross country policy heterogeneity should play a relatively minor role as an explanation for ambiguous findings. On the other hand, by using a uniform modeling strategy for the entire cross section, artificial heterogeneity in the findings across economies can be avoided. As a side benefit, we can consider a higher number of economies since analysis is not restricted to the cases where long sampling periods of monthly data are available.

This chapter is organised as follows. In Section 4.2, we introduce the econometric model. In Section 4.3, we discuss estimation results and provide model diagnostics along with robustness checks, Section 4.4 summarises our findings.

4.2 Model framework

In this Section, we describe our empirical strategy to test for theoretically asserted causal relations. We adopt the GARCH-M modeling approach as one of the most widely used means to express such relations. This makes our results largely comparable to those from a large part of the related literature. We further include a suitable set of control variables into the model to enable a meaningful economic interpretation of the causal relations under investigation.

4.2.1 The bivariate GARCH-in-mean model

For economies $i = 1, ..., N$, the bivariate GARCH specification for conditional second moments in inflation and output is modeled as

$$\begin{aligned} H_{it} &= C_i'C_i + F_i'e_{i,t-1}e_{i,t-1}'F_i + G_i'H_{i,t-1}G_i, \quad \text{with} \qquad (4.1)\\ F_i &= \begin{bmatrix} f_{i11} & f_{i12} \\ f_{i21} & f_{i22} \end{bmatrix}, \; G_i = \begin{bmatrix} g_{i11} & g_{i12} \\ g_{i21} & g_{i22} \end{bmatrix} \text{ and } \; H_{it} = \begin{bmatrix} h_{it}^{(\pi)} & h_{it}^{(\pi y)} \\ h_{it}^{(\pi y)} & h_{it}^{(y)} \end{bmatrix}. \end{aligned}$$

Accordingly, H_{it} represents uncertainties in inflation and output, while elements of F_i and G_i characterise the impact of shocks to inflation and output growth and past inflation and output uncertainties, respectively, on H_{it}. Surprises in inflation and output, being denoted as $e_{it} = (e_{it}^{(\pi)}, e_{it}^{(y)})' = H_{it}^{1/2}u_{it}$, $u_{it} \sim (0, I_2)$, are implied by the VAR model

$$\begin{aligned} \begin{pmatrix} \pi_{it} \\ y_{it} \end{pmatrix} &= \boldsymbol{\mu} + \sum_{p=1}^{P} \underbrace{\begin{bmatrix} \gamma_{ip}^{(\pi)} & \gamma_{ip}^{(y\pi)} \\ \gamma_{ip}^{(\pi y)} & \gamma_{ip}^{(y)} \end{bmatrix}}_{\Gamma_{ip}} \begin{pmatrix} \pi_{i,t-p} \\ y_{i,t-p} \end{pmatrix} + \sum_{q=1}^{Q} \underbrace{\begin{bmatrix} \psi_{iq}^{(oil)} & 0 \\ 0 & \psi_{iq}^{(\bar{y})} \end{bmatrix}}_{\Psi_{iq}} \begin{pmatrix} oil_{i,t-q} \\ \bar{y}_{t-q} \end{pmatrix} + \\ &+ \underbrace{\begin{bmatrix} \lambda_{i}^{(\pi)} & \lambda_{i}^{(y\pi)} \\ \lambda_{i}^{(\pi y)} & \lambda_{i}^{(y)} \end{bmatrix}}_{\Lambda_i} \begin{pmatrix} \sqrt{h_{it}^{(\pi)}} \\ \sqrt{h_{it}^{(y)}} \end{pmatrix} + \begin{pmatrix} e_{it}^{(\pi)} \\ e_{it}^{(y)} \end{pmatrix}, \qquad (4.2) \end{aligned}$$

where $\boldsymbol{\mu} = (\mu_1, \mu_2)'$ denotes a vector of intercept terms. The parameter matrices Γ_{ip} captures linkages between the levels of inflation and output. It is often argued that, apart from idiosyncratic influences, these variables may be driven by factors that are determined from outside the domestic economy. Two of the most important factors are oil prices or commonalities in business cycles among open economies (Ciccarelli and Mojon 2010). The latter determinant is expressed as $\bar{y}_{t-1} = (1/N)\sum_{i=1}^{N} y_{i,t-1}$, i.e. the average over economy-specific output growth rates. Potential impacts of $oil_{i,t-1}$ and $\bar{y}_{t-1}$ are represented by means of the parameters in Ψ_{iq}, whereas the effect of inflation and output uncertainties $\sqrt{h_{it}^{(\pi)}}$ and $\sqrt{h_{it}^{(y)}}$ is quantified in terms of the matrix Λ_i.

4.2.2 Inference

To account for the heterogeneity inherent in country-specific inflation and output dynamics, the system (4.1) and (4.2) is estimated individually for each economy. To summarise the findings regarding parameters obtained in this way for particular economies, the mean-group (MG) estimation method as introduced by Pesaran and Smith (1995) is employed.

In the following, let ϑ_i represent any parameter from (4.1) or (4.2) for economy i. The MG estimator then reads as

$$\bar{\vartheta} = \frac{1}{N}\sum_{i=1}^{N} \vartheta_i. \tag{4.3}$$

In contrast to most other panel techniques, the MG estimator does not rely on the assumption of cross sectional parameter homogeneity. According to Pesaran and Smith (1995), the estimator in (4.3) is consistent for large N and T in dynamic models. As an indication of whether relations in (4.1) and (4.2) feature qualitatively similar parameters over the cross section, we evaluate mean group $t-$ratios. The cross sectional $t-$statistic allows for accurate inference even in cases of nonstationary variables and small to moderate degrees of correlation among economy-specific equations (Coakley et al. 2001). Significance of mean group diagnostics indicates that a particular parameter estimate tends to be positive (or negative) across distinct types of economies. Since our interest focuses on robust cross country economic effects, we do not discuss country specific estimates in detail.

4.2.3 Implementation

For all countries, the lag orders in (4.2) are chosen as $P = 12$ and $Q = 3$. In (4.1), the 2×2 parameter matrices F_i and G_i are fully parameterized, while their respective upper left elements f_{11} and g_{11} are restricted to be positive to guarantee the identification of parameters (Engle and Kroner 1995). Proceeding in this way we allow for cross-equation linkages of second order dynamics in (4.1). Formulating the bivariate GARCH model in (4.1) as a BEKK specification (Engle and Kroner 1995) obtains parameter estimates in terms of nonlinear functions. For this reason we report empirical results for estimates of F_i and G_i by reformulating BEKK-implied results in terms of the so-called half-vec form (Bollerslev et al. 1988) that enables straightforward interpretation.[1] The system as described in (4.1) and (4.2) is estimated for each country $i = 1, \ldots, 34$ individually by numerical optimization of the likelihood function regarding model disturbances u_{it}. Owing to potential nonnormality of u_{it}, resulting quantifications of causality coefficients are regarded as Quasi-Maximum-Likelihood estimates (Comte and Lieberman 2003).

[1] For this purpose, define $h_t \equiv vech(H_t)$ and $\nu_t \equiv vech(e_t e_t')$, omitting country indices for notational convenience. Then, equation (4.1) might be reformulated in terms of $h_t = c + F^* \nu_{t-1} + G^* h_{t-1}$, deriving model parameters $M^* \in \{F^*, G^*\}$ from their counterparts $M \in \{F, G\}$ in (4.1) as follows:

$$M^* = \begin{bmatrix} m_{11}^2 & 2m_{11}m_{21} & m_{21}^2 \\ m_{11}m_{12} & m_{21}m_{12} + m_{11}m_{22} & m_{21}m_{22} \\ m_{12}^2 & 2m_{12}m_{22} & m_{22}^2 \end{bmatrix}.$$

For example, noting that $h_t = (h_{it}^{(\pi)} \; h_{it}^{(\pi y)} \; h_{it}^{(y)})'$, the lower left element given by m_{12}^2, where $m_{12}^2 \in \{g_{12}^2, f_{12}^2\}$, quantifies the nonnegative effect that lagged inflation uncertainty/ lagged inflation shocks exerts on output uncertainty.

4.3 Results

4.3.1 Causal linkages

In this Section, we analyse the outcomes of the model (4.1)-(4.2) over the considered set of economies. By means of studying parameter variation across economies, we investigate the strength of evidence for the hypotheses summarized in table 3.1. Furthermore, we discuss mean impulse response functions (IRFs) regarding surprises in inflation and output.[2] Proceeding in this way we highlight potential causal linkages with emphasis on a more detailed description of the shock response of the variables in question. Mean group estimates regarding relations between output and inflation from VAR estimates in (4.2) are reported in Table 4.1. To summarize the informational content of VAR coefficients, we further provide cross sectional averages of country specific impacts accumulated over the initial three (twelve) lags, denoted as $\sum_{l=1}^{3}$ (or $\sum_{l=1}^{12}$, respectively). The numbers in parentheses represent cross-sectional t-statistics. The table also contains the effects of uncertainty variables in H_{it} on the levels of output and inflation, whereas accumulated IRFs are depicted in Figure 4.1. A discussion of diagnostic tests regarding the model specification follows.

[2] The underlying country specific impulse response functions for GARCH-M models are calculated according to Elder (2003, 2004).

Table 4.1: Mean group estimates for model (4.1) respectively (4.2)

Eq		π_t			y_t	
l	y_{t-l}	π_{t-l}	oil_{t-l}	y_{t-l}	π_{t-l}	$\bar{y}_{t-l}$
1	0.0051	0.1806	0.0047	−0.3815	0.1572	0.1855
	(1.366)	(4.196)	(7.775)	(−7.235)	(1.138)	(2.982)
2	0.0042	0.0238	0.0003	−0.2249	−0.0392	0.3636
	(1.105)	(1.233)	(0.000)	(−5.886)	(−0.416)	(0.364)
3	0.0064	0.0644	0.0006	−0.1350	0.1330	0.3791
	(3.047)	(4.067)	(1.050)	(−4.449)	(1.087)	(5.920)
4	0.0107	0.0416	-	−0.0447	0.0177	-
	(4.504)	(3.493)		(−1.938)	(0.146)	
5	0.0047	0.0402	-	0.0205	−0.2833	-
	(1.316)	(3.203)		(1.294)	(−2.322)	
6	0.0041	0.0606	-	0.0457	−0.1228	-
	(2.019)	(4.706)		(2.214)	(−1.284)	
7	0.0026	0.0465	-	−0.0015	−0.1474	-
	(1.070)	(3.463)		(−0.079)	(−1.421)	
8	0.0061	0.0526	-	−0.0079	−0.0610	-
	(2.151)	(3.841)		(−0.417)	(−0.579)	
9	−0.0034	0.0400	-	0.0351	−0.1324	-
	(−1.213)	(3.205)		(1.831)	(−1.047)	
10	−0.0006	0.0585	-	−0.0296	−0.1446	-
	(−0.237)	(3.533)		(−1.950)	(−1.033)	
11	−0.0017	0.0647	-	−0.0403	−0.0046	-
	(−0.692)	(4.629)		(−2.325)	(−0.040)	
12	−0.0001	−0.0725	-	−0.0273	−0.3370	-
	(−0.039)	(−2.956)		(−1.484)	(−2.375)	
$\sum_{l=1}^{3}$	0.0157	0.2688	0.0056	−0.7415	0.2509	0.9282
	(2.170)	(5.317)	(5.507)	(−7.604)	(1.206)	(6.476)
$\sum_{l=1}^{12}$	0.0381	0.6010	-	−0.7916	−0.9646	-
	(3.560)	(11.966)		(−6.128)	(−3.424)	
h_t	0.0329	−0.4616	-	−0.2146	−2.9505	-
	(0.647)	(−1.298)		(−0.507)	(−2.848)	

The results given in Table 4.1 show that inflation and output are significantly related. In case of the impact of productivity growth on inflation quantified by $\bar{\gamma}_{ip}^{(y\pi)}$, most lag coefficients are positive, where four out of 12 are significant. The lag parameters $\bar{\gamma}_{ip}^{(\pi y)}$, which capture the effect of inflation on output tend to be negative, while being significant in two cases. Cross sectional averages of accumulated quarterly impacts are $\bar{\gamma}_3^{(y\pi)} = 0.016$ and $\bar{\gamma}_3^{(\pi y)} = 0.25$, respectively, where only the former estimate is significant. Accumulating over all lag coefficients up to one year, however, results in estimates $\bar{\gamma}_{12}^{(y\pi)} = 0.04$ and $\bar{\gamma}_{12}^{(\pi y)} = -0.96$ that are both significant at the 1% level. Thus, a 1% increase in output growth has an associated inflation effect of only 4 basis points, whereas an increase in inflation by 1% is followed by a decrease in output of almost 1%.[3] In terms of empirical magnitude, therefore, the estimated effect of inflation on output appears by far more relevant than the impact that output exerts on inflation. However, the influence that output exerts on inflation is found to be more systematic across economies and also takes, on average, less time to become evident than the reverse effect. This impression is confirmed by the accumulated (long run) IRFs depicted in Figure 1, where a surprise in output tends to be followed by a rise in the price level relatively quickly.

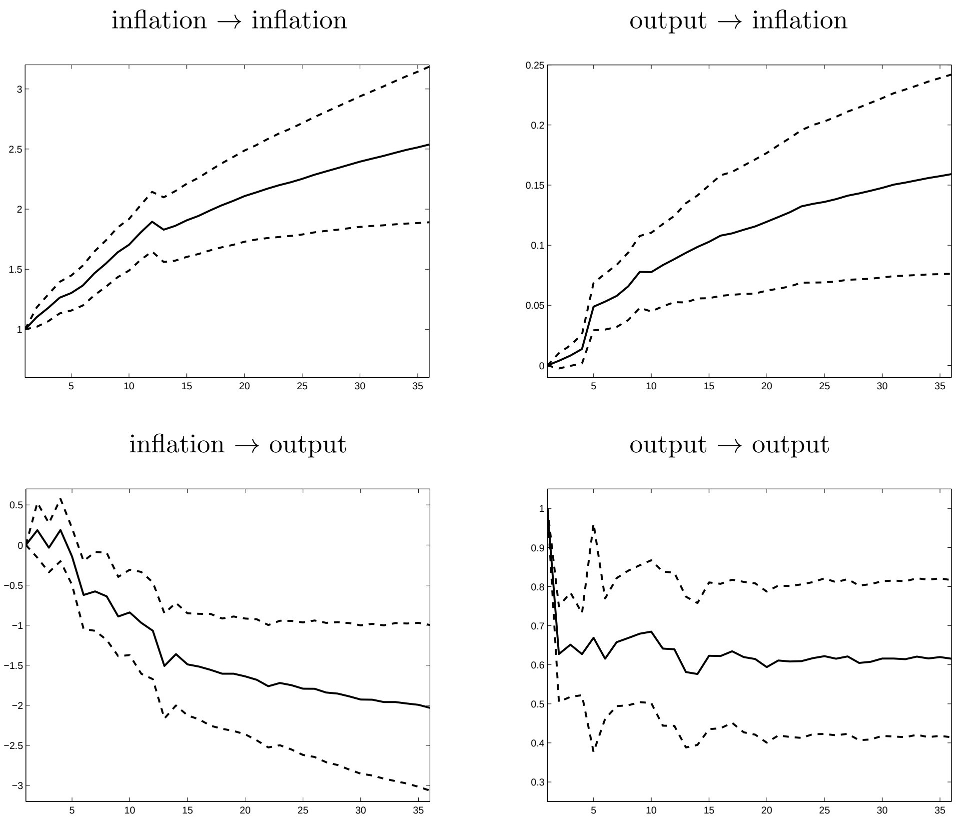


Fig. 4.1: Accumulated impulse response functions, on average across economies.
Dashed lines indicate approximate confidence bands based on ±2 standard deviations.

[3] A negative impact of inflation on output growth is in line with empirical studies such as Barro (1996), Gillman et al. (2005), Khan and Senhadji (2001) or Temple (2000).

Though occurring with a time lag, however, a large fraction of the impact of a surprise in inflation on output materialises during the first year after the shock. Our results suggest that, though the effect of output on inflation can be found almost immediately and reliably across economies, the consequences of excess inflation might be of greater economic importance in low-inflation economies. Hence, one might conjecture that, in economies that tend to be characterised by well anchored inflation expectations, inflation is not overly sensitive to economic activity, but output growth is more strongly affected by excess inflation. The estimated inflation effect on output growth appears even more relevant when it is compared, for instance, to the accumulated effect of the global average output growth on domestic growth rates $\bar{\psi}_3^{(\bar{y})}$. The response of domestic growth to the world business cycle has the same magnitude as the respective inflation effect. Hence, on average over the considered cross section, the output loss due to a moderate increase in inflation might be comparable to the one incurred in case of a 1% decrease in average world output growth. Moreover, we find considerable support for an adverse effect of IU on output growth. In 27 out of 34 economies, we observe negative coefficient estimates for the linkage between IU and output growth rates. The average effect of IU on output growth is $\bar{\lambda}^{(\pi y)}$=-2.95, with the associated t-ratio indicating significance at the 1% level. To provide a benchmark, annualized US inflation and production have unconditional means of about 2.7 % and 1.7%, whereas the unconditional standard deviations amount to 0.27 % and 0.8% for inflation and output growth, respectively. Accordingly, the statistically significant negative influences of inflation and inflation uncertainty on the growth rate of industrial production also appear to be relevant in terms of economic magnitude. Put differently, an effect of both inflation and IU on the real economy can be observed for a considerable part of the cross section. In the related literature, the effects of inflation and IU are often not treated separately as it is often presumed that a strong linkage exists between the two variables. The results in Table 4.1, however, suggest that potential disadvantages may arise from IU in addition to effects associated with the level of inflation. On the other hand, the hypotheses which suggest an impact of IU on inflation cannot be confirmed noting that the coefficient average $\bar{\lambda}^{(\pi)}$ is insignificant even at the 10% nominal level. Moreover, in contrast to Fountas et al. (2002), we do not find evidence for the hypothesis that OU is negatively related to output growth. From this we conclude that stabilization objectives do not seem to be beneficial regarding the level of output growth.

Table 4.2: Further mean group estimates for equation (4.1)

half-vec dynamics of VAR(12) residuals						
	$e_{t-1}^{(\pi)2}$	$e_{t-1}^{(\pi)}e_{t-1}^{(y)}$	$e_{t-1}^{(y)2}$	$h_{t-1}^{(\pi)}$	$h_{t-1}^{(\pi y)}$	$h_{t-1}^{(y)}$
Eq						
$h_t^{(\pi)}$	0.3173	0.0106	0.0014	0.3422	0.0050	0.0004
	(7.485)	(2.154)	(2.107)	(6.049)	(1.333)	(2.529)
$h_t^{(\pi y)}$	0.0046	0.1796	−0.0000	0.0049	0.3436	0.0027
	(1.918)	(8.625)	(−0.009)	(0.451)	(7.365)	(1.282)
$h_t^{(y)}$	0.0023	0.0104	0.1697	0.0058	0.0143	0.4376
	(2.814)	(1.873)	(6.417)	(1.703)	(0.795)	(8.358)

Summarising evidence regarding linkages among IU and OU in an analogous way, corresponding mean group parameters are reported in Table 4.2. Due to the positivity restriction imposed on the spillover parameters in the framework of the BEKK specification, significance of these coefficients (assessed by cross-sectional t-statistics) is less meaningful from the perspective of economic relevance. In contrast, the finding of an insignificant effect of IU on OU amounts to rather strong evidence against the hypothesis that IU impacts on OU. In line with Grier et al. (2004), however, the reverse effect of OU on IU and lagged idiosyncratic influences are throughout significant, yet they are numerically small. Finally, we document that modeling relations between the nominal and real economy by means of the particular model (4.1)-(4.2) is not only guided by the demand for a parametrisation of the economic hypotheses in question. It seems also justified from an empirical perspective, i.e. by means of diagnostic tests regarding the model specification. Firstly, multivariate ARCH-LM tests are considered to judge the effectiveness of the specification (4.1) in expressing the evolution of inflation and output uncertainties. Second, we employ multivariate LM test statistics (Breusch 1978; Godfrey 1978; Lütkepohl, 2005), to test for serial correlation up to order 6 in the standardised residuals $u_{it} = H_{it}^{-1/2} e_{it}$. Table 4.3 summarises the diagnostic test results across economies, where asterisks indicate significance at the 1% level. The abbreviation 'SC' refers to results of the serial correlation test results. For almost all countries in the cross section, neither ARCH effects nor autocorrelations can be detected in u_{it}.

Table 4.3: Multivariate diagnostics for standardized residuals

	SC	ARCH		SC	ARCH		SC	ARCH
AG	19.1	65.7	HN	20.7	34.1	NW	26.3	31.9
AT	26.1	80.7	IN	24.2	52.4	PT	33.3	39.0
BB	28.6	73.5	IR	28.6	33.6	PE	40.0	73.8
BG	39.8	59.8	IS	56.2*	62.8	PO	21.2	57.4
BR	36.4	63.40	IT	41.1	43.4	ES	30.0	48.9
CA	48.1*	31.9	JO	20.1	54.9	SD	35.3	30.0
CO	29.7	48.0	JP	27.5	30.6	TK	24.8	56.8
DK	31.8	47.3	KO	23.8	64.9	TW	38.0	47.0
FN	38.8	47.6	LU	38.3	79.2	UK	43.9*	100.1*
FR	35.7	43.9	MX	24.4	27.1	US	31.9	45.0
DE	27.8	36.6	MY	38.2	43.9	-	-	-
GR	47.1*	54.3	NL	26.6	61.7	-	-	-

The full names of individual economies are listed in table 2.2.

4.3.2 *Causal linkages for distinct subsamples*

In addition to the discussion of results for the entire cross section, we investigate results obtained by consideration of particular subgroups in the following. Several theoretical contributions postulate that causal relationships among inflation, output and respective uncertainties might be influenced by certain characteristics of the economies in question. In particular, one might consider the average inflation rate over longer time periods or an economy's participation in a currency union like the EMU as a determinant of causal linkages. Consideration of subset cross sections serves as an indication for the credibility and record of the respective economies' monetary authorities in anchoring inflation expectations. To investigate on whether estimates differ systematically across subgroups of economies, we examine coefficient averages regarding particular subgroups of economies. Firstly, respective subgroups are defined with respect to their members' average inflation rates, $\bar{\pi}_{i\cdot}^{(*)} = (1/T)\sum_{t=1}^{T} \pi_{it}$, where $* \in \{\text{low, intermediate, high}\}$ indicates membership in either group of lower-, medium or higher-inflation economies. We distinguish

$$\bar{\pi}_{i\cdot}^{(\text{low})} \leq d_{\text{low}} < \bar{\pi}_{i\cdot}^{(\text{int})} \leq d_{\text{int}} < \bar{\pi}_{i\cdot}^{(\text{high})}, \tag{4.4}$$

with $d_{\text{low}} = 2.5,\ d_{\text{int}} = 5$ as demarcation values. Subgroup specific parameter averages $\bar{\vartheta}_*$ obtain as averages over N_* economies as in the case of (4.3) for the entire cross section. To assess the significance of differences in coefficients in a pairwise subsample comparison we employ the two-sample t-statistic

$$t_{a,b} = \frac{\bar{\vartheta}_a - \bar{\vartheta}_b}{\sqrt{\frac{1}{N_a - 1}\sigma_a^2 + \frac{1}{N_b - 1}\sigma_b^2}}, \text{ where } (a, b) \in \{(\text{low,int}),(\text{low,high}),(\text{int,high})\}, \tag{4.5}$$

and σ_*^2 denotes the cross sectional variance within subgroups. Table 4.4 provides mean parameter estimates and $t-$statistics for the model described in (4.1) and (4.2) within subgroups. Most of the effects documented in the previous section cannot be rejected to be equal across economies with distinct inflation experiences. However, in lower-inflation economies, real effects of inflation appear to be stronger. Compared to medium and higher-inflation economies, inflation tends to be followed by higher economic growth in the subsequent quarter. In turn, over the rest of the year, the reduction of output growth is significantly more pronounced both in terms of size and significance of respective coefficients. This is in line with theoretical assertions of Gillman and Kejak (2004).

Table 4.4: Subsample estimates and mean differences

Eq.	coef.	low	int.	high	low-int.	low-high	int.-high
π	$\sum_1^3 \gamma^{(y\pi)}$	0.0202	0.0139	0.1951	0.0063	−0.1749	−0.1811
		(2.149)	(1.199)	(1.147)	(0.434)	(−1.145)	(−1.037)
	$\sum_1^{12} \gamma^{(y\pi)}$	0.0368	0.0387	0.1630	−0.0019	−0.1262	−0.1243
		(2.147)	(2.324)	(1.371)	(−0.080)	(−1.167)	(−1.012)
	$\sum_1^3 \gamma^{(\pi)}$	0.0404	0.2636	0.4981	−0.2232	−0.4577	−0.2345
		(0.677)	(3.840)	(6.645)	(−2.516)	(−4.948)	(−2.351)
	$\sum_1^{12} \gamma^{(\pi)}$	0.4132	0.5475	0.8471	−0.1343	−0.4340	−0.2996
		(7.786)	(5.640)	(19.593)	(−1.320)	(−6.326)	(−2.987)
	$\lambda^{(y\pi)}$	0.0082	0.0197	0.1478	−0.0115	−0.1395	−0.1280
		(0.153)	(0.133)	(1.227)	(−0.082)	(−1.142)	(−0.694)
	$\lambda^{(\pi)}$	0.0557	−1.2147	−0.2601	1.2703	0.3158	−0.9546
		(0.248)	(−1.056)	(−1.141)	(1.257)	(1.003)	(−0.875)
	$\sum_1^3 \psi^{(oil)}$	0.0044	0.0083	0.0036	−0.0039	0.0008	0.0047
		(3.563)	(3.268)	(2.640)	(−1.517)	(0.458)	(1.724)
y	$\sum_1^3 \gamma^{(y)}$	−0.7178	−0.7196	−0.6191	0.0018	−0.0986	−0.1004
		(−4.054)	(−4.435)	(−2.817)	(0.007)	(−0.361)	(−0.371)
	$\sum_1^{12} \gamma^{(y)}$	−0.7446	−0.6442	−0.7403	−0.1004	−0.0043	0.0961
		(−3.423)	(−2.788)	(−2.780)	(−0.321)	(−0.013)	(0.277)
	$\sum_1^3 \gamma^{(\pi y)}$	0.8861	−0.0857	−0.1442	0.9718	1.0303	0.0585
		(2.045)	(−0.268)	(−1.260)	(1.746)	(2.176)	(0.183)
	$\sum_1^{12} \gamma^{(\pi y)}$	−1.8931	−0.7182	−0.0824	−1.1748	−1.8106	−0.6358
		(−3.363)	(−1.863)	(−0.352)	(−1.653)	(−2.846)	(−1.477)
	$\lambda^{(y)}$	0.1973	−0.8223	−0.2569	1.0196	0.4542	−0.5654
		(0.522)	(−0.656)	(−0.479)	(0.888)	(0.724)	(−0.440)
	$\lambda^{(\pi y)}$	−2.2340	−5.5277	−1.4148	3.2937	−0.8192	−4.1129
		(−1.980)	(−1.905)	(−1.206)	(1.188)	(−0.513)	(−1.396)
	$\sum_1^3 \psi^{(\bar{y})}$	1.0705	0.7117	0.7040	0.3588	0.3665	0.0077
		(4.975)	(2.890)	(2.867)	(1.124)	(1.152)	(0.023)
$h^{(\pi)}$	$f^{(y\pi)}$	0.0011	0.0031	0.0001	−0.0020	0.0009	0.0030
		(1.714)	(1.511)	(2.107)	(−1.087)	(1.426)	(1.568)
	$f^{(\pi)}$	0.3252	0.1983	0.3904	0.1269	−0.0652	−0.1921
		(4.713)	(2.973)	(5.580)	(1.324)	(−0.675)	(−2.029)
	$g^{(y\pi)}$	0.0001	0.0011	0.0002	−0.0009	−0.0000	0.0009
		(2.560)	(2.055)	(2.049)	(−2.082)	(−0.109)	(1.887)
	$g^{(\pi)}$	0.2498	0.4229	0.3782	−0.1731	−0.1285	0.0446
		(2.873)	(4.057)	(3.557)	(−1.315)	(−0.967)	(0.306)
$h^{(y)}$	$f^{(y)}$	0.1684	0.1699	0.2204	−0.0015	−0.0520	−0.0505
		(3.099)	(3.684)	(3.751)	(−0.021)	(−0.664)	(−0.684)
	$f^{(\pi y)}$	0.0014	0.0037	0.0019	−0.0023	−0.0005	0.0018
		(1.406)	(1.771)	(1.678)	(−1.074)	(−0.319)	(0.793)
	$g^{(y)}$	0.3560	0.5219	0.4111	−0.1659	−0.0550	0.1108
		(3.746)	(5.980)	(4.618)	(−1.278)	(−0.426)	(0.909)
	$g^{(\pi y)}$	0.0013	0.0121	0.0053	−0.0108	−0.0040	0.0068
		(1.502)	(1.200)	(1.015)	(−1.251)	(−0.840)	(0.628)

This means that in higher-inflation economies, the marginal impact of inflation on output growth is comparably smaller than an increase in an economy which has been characterized by low average inflation beforehand. Impulse responses depicted in Figure 2 illustrate the characteristic dynamics of output that tend to follow inflation shocks.

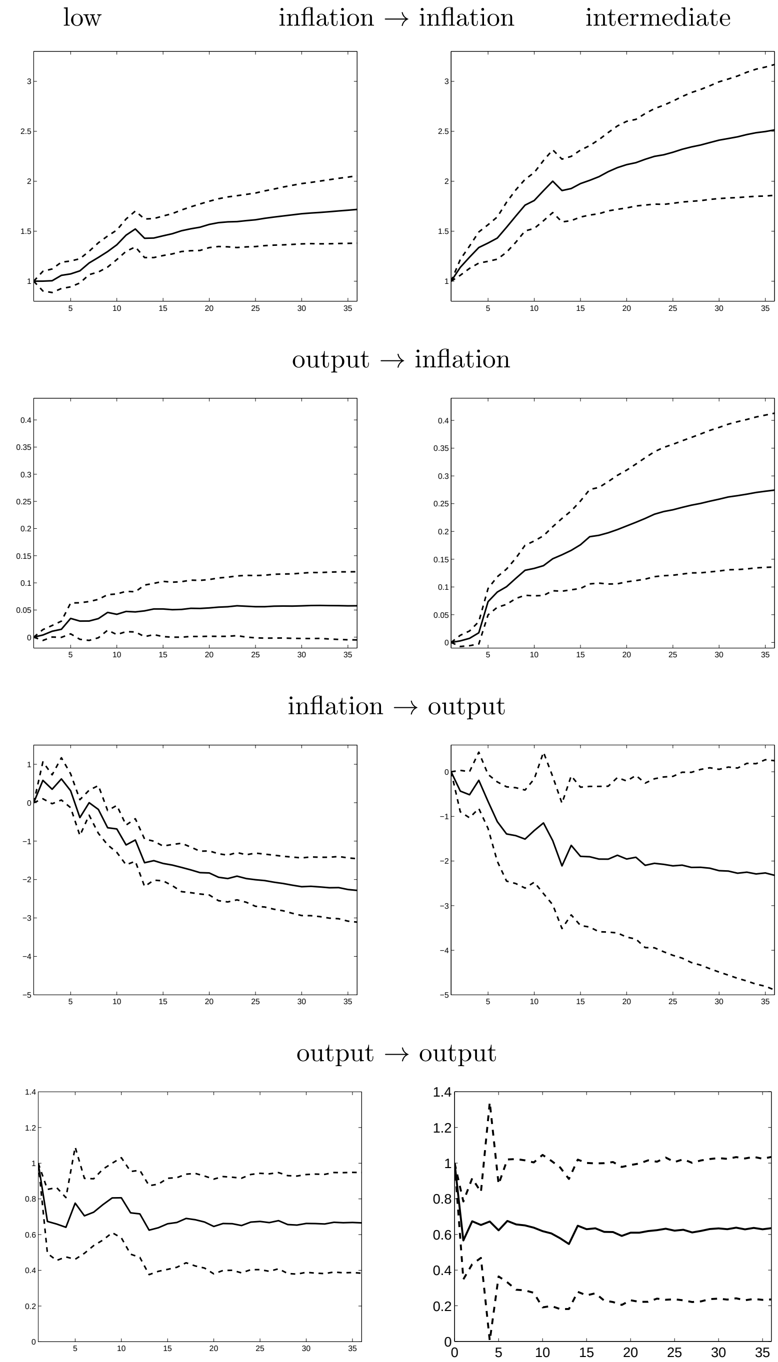


Fig. 4.2: Average accumulated impulse response functions for subgroups
Considered subgroups are economies with low (< 2.5%) and intermediate inflation rates (between 2.5% and 5%). For further descriptions see Figure 1.

By comparing the IRFs for low- and intermediate inflation regimes[4], it can be seen that the relation is most clear-cut for the lower-inflation economies. This subgroup is characterised by a particularly low standard deviation across IRFs. In turn, IRFs further suggest that inflation tends to rise more strongly after a positive output shock in medium inflation economies compared to lower-inflation economies. However, the effect of IU on output growth does not significantly differ across economies with distinct inflation experiences. Influences of predetermined variables oil_{t-1} and $\bar{y}_{t-1}$ are throughout invariant with respect to distinct average inflation levels. Moreover, volatility spillovers as obtained in the previous section also appear to be unaffected by the average level of inflation in the respective economies. Both the insignificance of the IU impact on output growth uncertainty and the significance of the other coefficients expressing uncertainty linkages are robust with respect to the consideration of distinct subgroups. We conclude that relations depend on past inflation experience only in a quantitative manner.

[4] We do not consider impulse response functions for higher-inflation economies. Given that inflation rates in 6 out of 11 higher-inflation economies are nonstationary, an aggregation of country specific impulse responses appears less meaningful.

Table 4.5: Subsample estimates and mean differences: EMU vs. EU5 and $O17$

	EMU(a)	EU5(b)	$O17$(c)	(a)-(b)	(a)-(c)	(b)-(c)
Dependent var.: π						
$\sum_1^3 \gamma^{(y\pi)}$	0.0170	0.0394	0.0077	−0.0223	0.0093	0.0316
	(2.5221)	(2.3004)	(0.6173)	(−1.0947)	(0.6324)	(1.3702)
$\sum_1^{12} \gamma^{(y\pi)}$	0.0297	0.0523	0.0398	−0.0226	−0.0102	0.0124
	(2.6544)	(1.2614)	(2.3890)	(−0.4730)	(−0.4891)	(0.2517)
$\sum_1^3 \gamma^{(\pi)}$	0.1815	0.3347	0.3110	−0.1532	−0.1295	0.0237
	(3.6016)	(2.2947)	(3.6607)	(−0.8941)	(−1.2676)	(0.1280)
$\sum_1^{12} \gamma^{(\pi)}$	0.5820	0.6899	0.5883	−0.1079	−0.0063	0.1016
	(11.3344)	(4.3737)	(6.9693)	(−0.5853)	(−0.0615)	(0.5167)
$\lambda^{(y\pi)}$	0.0340	−0.0740	0.0635	0.1080	−0.0294	−0.1375
	(0.5267)	(−0.3718)	(0.8607)	(0.4647)	(−0.2894)	(−0.5847)
$\lambda^{(\pi)}$	0.0484	−0.3615	−0.8510	0.4100	0.8994	0.4895
	(0.1735)	(−0.7804)	(−1.2731)	(0.6897)	(1.2021)	(0.5679)
$\sum_1^3 \delta^{(oil)}$	0.0063	0.0006	0.0066	0.0057	−0.0003	−0.0060
	(6.3518)	(0.4052)	(3.7532)	(2.9060)	(−0.1575)	(−2.4431)
Dependent var.: y						
$\sum_1^3 \gamma^{(y)}$	−1.0105	−0.4474	−0.6382	−0.5631	−0.3723	0.1908
	(−7.5035)	(−5.2647)	(−4.0815)	(−3.3176)	(−1.7405)	(1.0198)
$\sum_1^{12} \gamma^{(y)}$	−1.0641	−0.2164	−0.7683	−0.8477	−0.2958	0.5519
	(−4.7178)	(−1.5178)	(−4.2134)	(−2.9803)	(−0.9813)	(2.2395)
$\sum_1^3 \gamma^{(\pi y)}$	0.8590	0.7731	−0.3319	0.0859	1.1909	1.1050
	(3.3799)	(0.7713)	(−1.8903)	(0.0746)	(3.7068)	(0.9734)
$\sum_1^{12} \gamma^{(\pi y)}$	−1.4572	−0.7214	−0.6884	−0.7359	−0.7689	−0.0330
	(−2.2342)	(−1.9317)	(−2.2450)	(−0.9210)	(−1.0238)	(−0.0630)
$\lambda^{(y)}$	0.1157	−0.3711	−0.4017	0.4868	0.5174	0.0306
	(0.2167)	(−1.1368)	(−0.5255)	(0.7303)	(0.5360)	(0.0352)
$\lambda^{(\pi y)}$	−4.3184	−1.0992	−2.5295	−3.2192	−1.7889	1.4304
	(−2.1491)	(−0.7062)	(−1.7314)	(−1.1808)	(−0.6925)	(0.6216)
$\sum_1^3 \delta^{(\bar{y})}$	1.3870	0.7030	0.6707	0.6840	0.7163	0.0323
	(8.4153)	(3.2280)	(2.8940)	(2.2938)	(2.4327)	(0.0947)

Mean group diagnostics for model (4.1)-(4.2) obtained for distinct subgroups of economies in the European Monetary Union (EMU), EU members not in the EMU (EU5) and other economies ($O17$). The right hand side provides two-sample t-test statistics for pairwise comparisons of coefficient subgroup means according to (4.5).

Next, we compare causal effects for the member economies of the EMU to those EU member states which did not adopt the Euro and the other economies in the data set. In the following, these groups of economies are denoted as EMU, EU5 and $O17$, respectively. The distinction proceeds in analogy to the separation of inflation regimes described above[5]. In table 4.5, average coefficients for the subgroups and test outcomes for groupwise comparisons are reported. In general, causal effects are qualitatively similar for the considered subgroups. However, several significant quantitative differences are detected. First, the negative effect of IU on output growth as expressed by $\lambda^{(\pi y)}$ is

[5] We focus on the discussion of the two-sample t-tests to economise on space. Results for IRFs are available from the author on request.

only significant for the EMU member economies. These economies are thus affected by rising inflation risks in the strongest way. Similarly, EMU and $O17$ economies are more strongly exposed to oil price changes than the EU5 group. This can be seen from the estimates of $\sum_1^3 \delta^{(oil)}$. Moreover, significant differences in the accumulated effect of the global mean output growth rate $\sum_1^3 \delta^{(\bar{y})}$ on growth rates in respective economies reveals that the EMU and EU5 economies might be more closely linked to variation in the global business climate. However, the plots in figure 4.3 reveal that the EMU is still characterised by overall lower levels of IU than the other economies. This is the case both before and during the recent times since the emergence of the financial and sovereign debt crisis. The figure depicts average IU in the EMU (blue line), EU5 members (green line) and $O17$ economies (red line). The plots show that the repeated uprise in IU at the end of the sample period in the EU5 is not reflected in the IU experienced by the EMU. The issue of potential benefits of the EMU member states in terms of lower IU will be addressed more formally and by means of several alternative IU measures in chapter 8.

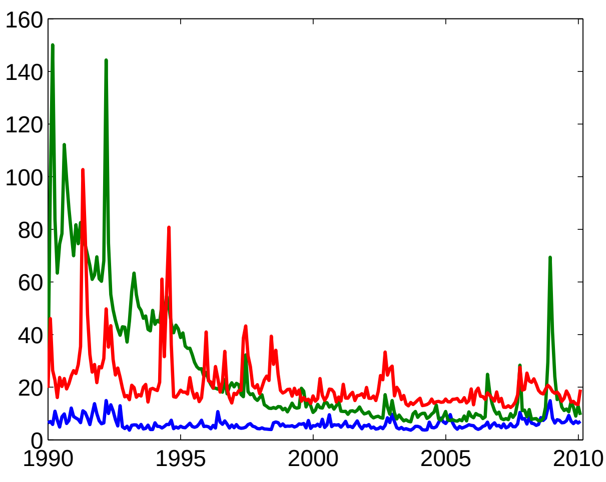


Fig. 4.3: Inflation uncertainty as measured by the GARCH model in equation (4.1).

4.4 Summary

In this chapter, the interaction of inflation, output and their uncertainties is assessed by means of a bivariate GARCH-in-mean model. Such models are commonly employed to conduct causal inference among these quantities in the related literature. We focus on the recent times when inflation targeting has been the predominantly adopted rule of monetary policy and consider a large cross section of 34 developed and emerging economies. We document marked influences of nominal quantities on output growth. Both the level of inflation and the associated uncertainty tend to lower output growth across a wide range of distinct economies. We further find that theoretical arguments regarding the dependency of causal linkages on the monetary policy framework are relevant for some of the relations we investigate. Particularly, the effects of inflation on output appear most pronounced for economies that put a high effort on keeping inflation low. However, the negative impact of inflation uncertainty on output growth appears to hold irrespective of the monetary regime. Furthermore, there exist significant spillover effects among uncertainties in output and inflation. Similarly, the participation of economies in the EMU affects mostly the magnitude of causal effects. The EMU economies are most strongly at risk of incurring reductions in output growth from excess IU. Higher growth rates of oil prices or reductions in the global business cycle, respectively, also impact on EMU economies in a more pronounced way than on the EU5 or O17 economies. Given these results, it is particularly remarkable that the EMU members are characterised by a lower overall level of IU than other economies. The IU level for members of the EU5 group, which converged towards IU in the EMU before 2008, experienced sharp increases in IU afterwards. This increase is not found in case of the EMU economies.

5. TWO GROUPS OF ALTERNATIVE INFLATION UNCERTAINTY (IU) MEASURES

The setup of GARCH models as in the preceding chapter is a common way of investigating causal relations involving uncertainty. However, several alternative methods have been proposed to measure the latent IU (or OU). It is unclear a priori which measure is most suitable for a certain investigation. Hence, prior to empirical investigations, it has to be decided which IU measure should be used. In the following, we firstly introduce alternative forecasting-based IU measures. Next, we conduct a comparative evaluation of distinct IU measures. After obtaining a ranking of IU measures, several important causal relations and the issue of state-dependence and the institutional impact on IU are examined by means of the most informative IU metrics. For this purpose, we consider specifications which mimic commonly used dynamic and disparity approaches. To obtain measures of disparity, we replace forecast survey data by model based predictions. Thus, distinct IU measures are conditional on sample information with equal timing. This is typically not the case when both survey data and aggregate time series are used to determine distinct expressions of IU. Surveyed experts might have access to more timely or private information while time series measures are confined to publicly available data (Rich and Tracy 2003). Moreover, it becomes possible to consider a larger cross section of economies if expert data is replaced by model forecasts. Finally, the models we propose do not require large samples of historical observations. A focus on recent data might account for potential changes in inflation regimes

(Evans and Wachtel 1993). In the following, eight distinct measures of IU are discussed. We firstly consider time series based methods. These approaches measure IU by drawing upon historical sample information. The second group comprises 4 approaches which are based on the dispersion of individual forecasts. With one exception, all measures are ex-ante quantifications of IU.

Two of the uncertainty measures are based on a specification widely used for inflation forecasting, the linear autoregressive (AR) model. The success of AR models or random walk schemes in predicting inflation is documented in several empirical studies, including Canova (2007) or Stock and Watson (2007, 2008). Autoregressive models do not explicitly incorporate inflation expectations as explanatory variables like it is common in structural models as, e.g. the NKPC. This might appear to be at odds with theoretical concepts of IU as mentioned in chapter 1 or Ball and Cecchetti (1990), where IU is introduced as the ex-ante risk of inaccurate inflation expectations. However, given the widely documented predictive success of random walk specifications, the AR model is regarded as a reliable approximation to the final form representation of models like the NKPC. Allowing for the possibility of local trends in the inflation series, the AR scheme is formulated as

$$\pi_{t+\ell} = \varphi_0 + \varphi_1 t + \varphi_2 \pi_t + \epsilon_{t+\ell}, \quad t = \tau - B + 1, ..., \tau, \tag{5.1}$$

where $\epsilon_{t+\ell} \overset{iid}{\sim} (0, \sigma_\epsilon^2)$, $\ell \in \{1, 2, 3, 4\}$ is the forecast horizon[1], and B denotes the length of the (rolling) estimation sample window[2]. Out-of-sample forecasts implied by (5.1) are denoted $\hat{\pi}_{\tau+\ell|\tau}$, with $\tau = T_0^* - \ell - P, ..., T^* - \ell$ denoting the rolling forecast origin. The time instances T_0^* and T^* delimit the sample

[1] This choice corresponds to horizons between 1 quarter and 1 year. If monthly data are considered in subsequent chapters, $\ell \in \{1, 3, 6, 12\}$.

[2] Extracting inflation expectations from higher-order AR specifications obtains qualitatively equivalent results which are available from the author upon request. Furthermore, note that the $\mathcal{M}18$, $\mathcal{M}22$ and $\mathcal{Q}18$ data sets, starting in 1988M1 comprise IU measures which are based on the AR or related forecasting models. Thus, the availability of B observations prior to 1988M1 is required.

periods on which the evaluation of alternative IU measures and causal analysis in subsequent chapters is based.

5.1 Dynamic specifications

1.1 Predictive standard deviation

At forecast origin τ, the estimated predictive error standard deviation obtained from (5.1) is

$$\hat{\sigma}_{\tau+\ell|\tau} = \tilde{\sigma}_{\epsilon}\sqrt{(1 + \boldsymbol{z}'_{\tau}(Z'_{\tau}Z_{\tau})^{-1}\boldsymbol{z}_{\tau})}, \tag{5.2}$$

where Z_τ is the autoregressive design matrix and $\boldsymbol{z}_\tau$ are the most recent observations employed to obtain out-of-sample forecasts. The statistic in (5.2) is composed of time-local expressions of the variance of inflation surprises and estimation uncertainty.

1.2 Exponential smoothing

Among the most prominent ways to measure IU are GARCH processes. To obtain ex-ante formulations of IU, however, this class of models is not uniformly recommendable (Hwang and Pereira 2006). As nonlinear specifications, estimated GARCH models are likely to suffer from inefficiencies if samples of moderate size are considered. We suggest an alternative which is designed to balance both the arrival of news and inertia in second-order inflation dynamics. Being related to the RiskMetrics exponential smoothing approach (Zangari 1996), this IU measure reads as

$$h^{(\xi)}_{\tau+1|\tau} = \sqrt{\xi(\Delta\pi_\tau)^2 + (1-\xi)\overline{(\Delta\pi)^2}}. \tag{5.3}$$

In (5.3), $\Delta\pi_t = \pi_t - \pi_{t-1}$, and $\overline{(\Delta\pi)^2} = (1/(B-1))\sum_{t=\tau-B+1}^{\tau-1}(\Delta\pi_t)^2$, where smoothing over past observations is restricted to express IU only by means of the most currently observed data[3]. To facilitate the IU quantification at the current end of sample information, we choose $\xi \in \{0.1, 0.2\}$ (Christoffersen and Diebold 2000). Such magnitudes are typically estimated by means of GARCH models for quarterly inflation data.

1.3 Unanticipated volatility

The statistics in (5.2) and (5.3) are obtained as ex-ante quantifications of IU. An alternative IU indicator might be obtained as the realised prediction error

$$\hat{a}_{\tau+\ell} = |\hat{\pi}_{\tau+\ell|\tau} - \pi_{\tau+\ell}|, \tag{5.4}$$

from the AR model in (5.1). This measure expresses the common view that the ex-post track record of inflation forecasting success (or loss) may serve as an indicator of currently perceived inflation risk (Giordani and Söderlind 2003).

5.2 Measuring IU by means of opinion disparity

A common way of measuring uncertainty is to exploit the variation across individual expectations. We model the dispersion of opinions by considering forecasts from $J = 5$ alternative linear forecasting specifications, i.e. the AR scheme in (5.1) and 4 additional models which are listed in the appendix.

2.1 Disagreement of expectations

Based on five rival predictions of inflation, the disagreement measure obtains

[3] Results based on alternative choices of B are qualitatively equivalent and available from the authors upon request.

as

$$\hat{s}_{\tau+\ell|\tau} = \sqrt{\frac{1}{J-1}\sum_{j=1}^{J}(\hat{\pi}_{j,\tau+\ell|\tau} - \overline{\pi}_{\tau+\ell|\tau})^2}, \tag{5.5}$$

with $\overline{\pi}_{\tau+\ell|\tau} = (1/J)\sum_{j=1}^{J}\hat{\pi}_{j,\tau+\ell|\tau}$. Variants of (5.5) are employed in numerous studies, e.g. Cukierman and Wachtel (1979) or Batchelor and Dua (1996). However, this measure is not always easily interpreted. First, it is not directly linked to idiosyncratic uncertainty (Pesaran and Weale 2006). Second, disagreement is at most one component of aggregate uncertainty, e.g. if the latter is derived from a set of density forecasts (Wallis 2005, Boero et al. 2008).

2.2 Average uncertainty

In addition to (5.5), Zarnowitz and Lambros (1987) propose to average individual predictive standard deviations. Adapted to the forecasting models that we consider, this measure obtains as

$$\bar{\sigma}_{\tau+\ell|\tau} = \frac{1}{J}\sum_{j=1}^{J}\hat{\sigma}_{j,\tau+\ell|\tau}, \tag{5.6}$$

with $\hat{\sigma}_{j,\tau+\ell|\tau}$ denoting predictive standard deviations obtained, e.g. according to (5.2) for the AR scheme in (5.1). The statistic $\bar{\sigma}_{\tau+\ell|\tau}$ is regarded as a dispersion IU measure like $\hat{s}_{\tau+\ell|\tau}$, since both entail characteristics which only arise as a matter of pooling. For example, $\bar{\sigma}_{\tau+\ell|\tau}$ is less likely to obtain an 'eccentric' (Zarnowitz and Lambros 1987) assessment of IU than its individual components. Moreover, as Zarnowitz and Lambros (1987) note, $\bar{\sigma}_{\tau+\ell|\tau}$ may be interpreted as a combination of IU forecasts. Forecast combination strategies for predictions of conditional second moments have been evaluated by Becker and Clements (2008) or by Patton and Sheppard (2009), who investigate volatility forecasts for the S&P500 index and IBM stock returns, respectively. In both cases, averages of single model based volatility forecasts as in (5.6) cannot be outperformed by any competing prediction scheme.

2.3 Augmenting the disagreement measure

As noted by Lahiri and Liu (2005), estimates of IU like $\hat{\sigma}_{\tau+\ell|\tau}$ in (5.2) might be characterised by individual biases. They suggest a combination of (5.5) and (5.6), given by[4]

$$\varsigma_{\tau+\ell|\tau} = 0.5(\hat{s}_{\tau+\ell|\tau} + \bar{\sigma}_{\tau+\ell|\tau}). \tag{5.7}$$

In cases when individual biases in $\hat{\sigma}_{j,\tau+\ell|\tau}$ are not symmetrically distributed around $\bar{\sigma}_{\tau+\ell|\tau}$, the resulting bias in (5.6) might be balanced by the disagreement term $\hat{s}_{\tau+\ell|\tau}$ in (5.7). For situations when surveyed experts report individual forecasts of density functions, Lahiri and Liu (2005) and Wallis (2005) point out the equivalence of this measure to the variance of combined density forecasts (cf. Diebold et al. 1999, Giordani and Söderlind 2005). Finally, Lahiri and Sheng (2010) propose a combination of disagreement measures and IU quantifications from GARCH models as a further ex-ante approximation of IU. We determine a similar combination measure as

$$\zeta_{\tau+\ell|\tau} = 0.5(\hat{s}_{\tau+\ell|\tau} + h^{(0.1)}_{\tau+1|\tau}), \tag{5.8}$$

where the exponential smoothing measure $h^{(0.1)}_{\tau+1|\tau}$ is regarded as a substitute to GARCH quantifications.

5.3 *Statistical properties of IU approximations*

Before turning to the assessment of IU measures' predictive ability, some features of the alternative IU statistics are discussed in the following. In particular, we examine their relative magnitudes, mutual correlations and correlations

[4] In Lahiri and Liu (2005), the scaling factor of 0.5 is not applied. We specify $\varsigma_{\tau+\ell|\tau}$ in this way to align our analysis with the literature on forecast combinations, where the sum of combination weights is typically constrained to unity.

with benchmark IU statistics. The boxplots in figure 1 show the magnitudes and variation of distinct IU approximations for the 18 sample economies. The plots depict averages of $IU_{\tau+\ell|\tau}$ over the period between 1988Q1 and 2011Q1. The numbers on the abscissa refer to the following IU measures: 1.) $\hat{\sigma}_{\tau+\ell|\tau}$, 2.) $h^{(0.1)}_{\tau+1|\tau}$, 3.) $h^{(0.2)}_{\tau+1|\tau}$, 4.) $\hat{a}_{\tau}$, 5.) $\hat{s}_{\tau+\ell|\tau}$, 6.) $\bar{\sigma}_{\tau+\ell|\tau}$, 7.) $\varsigma_{\tau+\ell|\tau}$, 8.) $\zeta_{\tau+\ell|\tau}$. Averages of the dynamic IU quantifications are multiplied by 5 to facilitate comparisons in one graph. The magnitudes of distinct IU quantifications are also compared in studies like Batchelor and Dua (1996) or Bomberger (1996). The relative magnitudes of the IU statistics considered in this study are similar to those reported by Batchelor and Dua (1996), Bomberger (1996) and Lahiri and Sheng (2010). Moreover, Lahiri and Sheng (2010) find that the variation in GARCH based IU quantifications is smaller than the one obtained from a disagreement measure. This relation is also reflected in our comparison between dynamic and dispersion IU statistics.

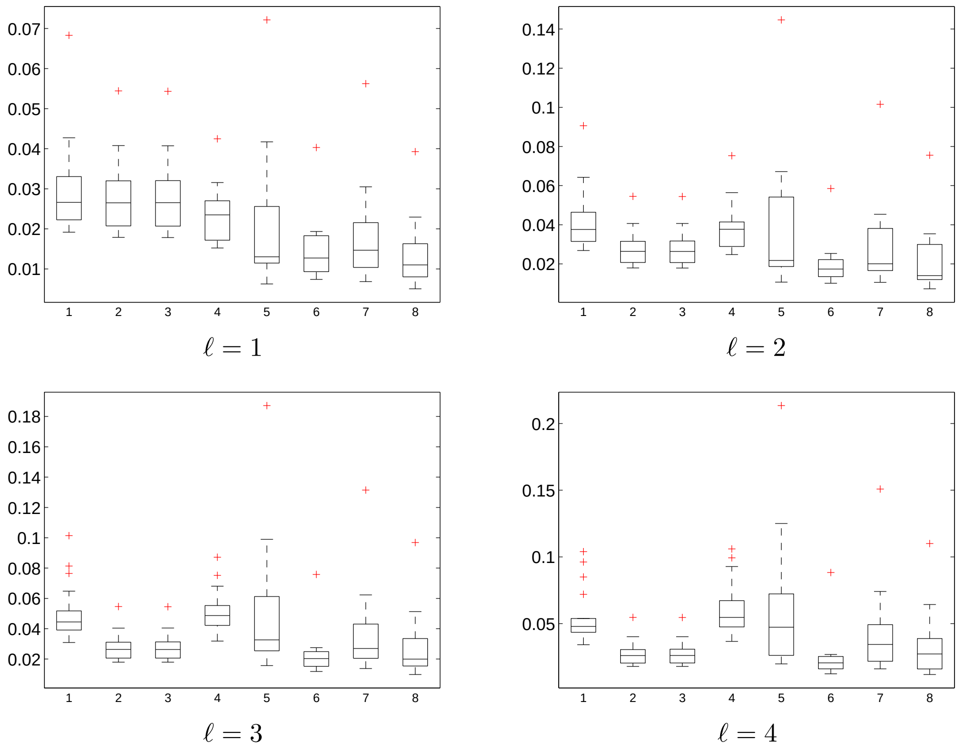


Fig. 5.1: Boxplots for average IU over 1988Q1 to 2011Q1, in 18 economies.

The number of distinct IU approximations discussed in the related literature is an indication for the difficulty to select a suitable IU measure. This ambiguity can be addressed by comparing a set of IU metrics which provide partly idiosyncratic information. Hence, we report correlations of alternative IU measures to examine their common and idiosyncratic characteristics. Respective correlation coefficients are reported in table 5.1. The a-priori classification of IU measures into dynamic and dispersion metrics is confirmed by the correlation numbers. Particularly high correlations are found between the dispersion measures $\hat{s}_{\tau+\ell|\tau}$, $\varsigma_{\tau+\ell|\tau}$ and $\zeta_{\tau+\ell|\tau}$. The linkages between time series based measures $\hat{\sigma}_{\tau+\ell|\tau}$, $h^{(\xi)}_{\tau+1|\tau}$ and $\hat{a}_\tau$ are smaller but still markedly positive.

Table 5.1: Mutual correlations of IU measures for $\ell = 1$

	$\hat{\sigma}_{\tau+\ell\vert\tau}$	$h^{(0.1)}_{\tau+1\vert\tau}$	$h^{(0.2)}_{\tau+1\vert\tau}$	$\hat{a}_{\tau}$	$\hat{s}_{\tau+\ell\vert\tau}$	$\bar{\sigma}_{\tau+\ell\vert\tau}$	$\varsigma_{\tau+\ell\vert\tau}$
$h^{(0.1)}_{\tau+1\vert\tau}$	0.70	·	·	·	·	·	·
$h^{(0.2)}_{\tau+1\vert\tau}$	0.69	0.98	·	·	·	·	·
$\hat{a}_{\tau}$	0.44	0.45	0.56	·	·	·	·
$\hat{s}_{\tau+\ell\vert\tau}$	0.39	0.13	0.12	0.11	·	·	·
$\bar{\sigma}_{\tau+\ell\vert\tau}$	0.45	0.19	0.18	0.09	0.72	·	·
$\varsigma_{\tau+\ell\vert\tau}$	0.45	0.16	0.15	0.11	0.97	0.85	·
$\zeta_{\tau+\ell\vert\tau}$	0.43	0.18	0.18	0.14	0.99	0.72	0.97

Cell entries represent average correlation coefficients across 18 economies.

In addition, we compare the model based IU metrics and two reference IU measures which are frequently employed in the related literature. As a first benchmark, we obtain GARCH(1,1) estimates (Bollerslev 1986). The correlation statistics of the model based IU metrics to the benchmark are reported in table 5.2. Similar to the $h^{(\xi)}_{\tau+1|\tau}$ measures, the GARCH estimates are only obtained for $\ell = 1$. For most of the 18 economies we find rather high and positive correlations between IU measures and GARCH. In particular, the IU measure $\bar{\sigma}_{\tau+\ell|\tau}$ is strongly related to the GARCH measure.

	$\hat{\sigma}_{\tau+1\|\tau}$	$h^{(0.1)}_{\tau+1\|\tau}$	$h^{(0.2)}_{\tau+1\|\tau}$	$\hat{a}_{\tau}$	$\hat{s}_{\tau+1\|\tau}$	$\bar{\sigma}_{\tau+1\|\tau}$	$\varsigma_{\tau+1\|\tau}$	$\zeta_{\tau+1\|\tau}$
Austria	-0.01	-0.20	-0.19	0.01	0.45	**0.58**	0.50	0.45
Belgium	0.07	-0.11	-0.09	0.01	0.20	**0.26**	0.23	0.18
Canada	-0.37	-0.17	-0.17	-0.18	0.17	**0.34**	0.21	0.16
Denmark	**0.17**	0.08	0.09	0.13	0.08	0.03	0.06	0.08
Finland	**0.42**	0.33	0.34	0.16	-0.14	0.17	-0.01	-0.11
France	-0.41	-0.18	-0.18	-0.29	-0.21	**0.02**	-0.16	-0.22
Germany	0.39	-0.09	-0.09	0.00	0.75	**0.83**	0.80	0.75
Ireland	**0.42**	0.11	0.10	0.02	0.26	0.04	0.21	0.26
Italy	**0.74**	0.28	0.31	0.48	0.31	0.38	0.36	0.31
Japan	0.49	-0.07	-0.08	0.00	0.68	0.65	**0.69**	0.68
Netherlands	**0.57**	0.26	0.27	0.11	0.30	0.43	0.36	0.31
Norway	0.15	0.35	0.36	0.23	0.46	**0.50**	0.48	0.46
Portugal	0.78	0.46	0.45	0.14	0.34	**0.83**	0.72	0.42
Spain	-0.72	-0.49	-0.46	-0.10	**0.03**	-0.06	0.01	0.01
Sweden	0.14	0.02	0.02	0.01	0.53	0.53	**0.54**	0.53
Switzerland	-0.01	-0.21	-0.21	-0.08	0.39	**0.44**	0.41	0.37
UK	0.45	0.04	0.03	0.01	0.59	**0.68**	0.62	0.59
US	-0.10	-0.24	-0.24	-0.15	0.08	**0.34**	0.15	0.05

Table 5.2: The entries denote correlations between distinct IU measures introduced in (2) to (8) for $\ell = 1$ and IU as implied by a GARCH(1,1) model. For each economy, the highest correlation between the benchmark and model based IU statistics appears in boldface. Respective results for $\ell > 1$ are qualitatively similar and available from the authors on request.

Furthermore, we examine how closely model based approaches are linked to survey based IU quantifications. The corresponding benchmark IU estimate is based on a survey of inflation expectations, provided by the Center for European Economic Research (ZEW) for the period 1992Q1 to 2011Q1. This data set reports percentages out of 350 respondents who expect inflation either to rise or to remain at most equal during the year after each wave of the survey. With $\hat{\mathcal{P}}$ denoting the fraction of respondents who expect a rising inflation rate, a survey based measure of IU is obtained as

$$u_{\tau+4|\tau} = \sqrt{\frac{\hat{\mathcal{P}}(1-\hat{\mathcal{P}})}{350}}. \tag{5.9}$$

In table 5.3, cell entries denote correlation coefficients between $u_{\tau+4|\tau}$ and the

IU measures (5.2) to (5.8).

	$\hat{\sigma}_{\tau+\ell\vert\tau}$	$h^{(0.1)}_{\tau+1\vert\tau}$	$h^{(0.2)}_{\tau+1\vert\tau}$	$\hat{a}_{\tau}$	$\hat{s}_{\tau+\ell\vert\tau}$	$\bar{\sigma}_{\tau+\ell\vert\tau}$	$\varsigma_{\tau+\ell\vert\tau}$	$\zeta_{\tau+\ell\vert\tau}$
$\ell = 1$								
Germany	0.09	0.39	**0.40**	0.26	-0.28	-0.20	-0.30	-0.26
France	0.17	0.06	0.10	0.21	0.35	**0.37**	0.37	0.37
Italy	-0.23	-0.24	-0.20	0.08	0.11	**0.14**	0.12	0.09
Japan	0.17	0.11	0.15	0.20	0.13	**0.20**	0.15	0.13
UK	0.04	0.18	0.22	**0.29**	-0.13	0.20	0.06	-0.12
US	0.12	0.21	0.24	**0.32**	-0.01	-0.00	-0.01	0.03
$\ell = 2$								
Germany	-0.11	0.36	**0.38**	0.18	-0.33	-0.36	-0.44	-0.31
France	0.08	-0.02	-0.00	-0.02	0.35	0.33	**0.36**	0.35
Italy	-0.12	-0.31	-0.29	0.08	0.23	0.23	**0.24**	0.23
Japan	0.15	0.02	0.07	0.12	0.31	0.32	**0.32**	0.31
UK	-0.01	0.05	0.09	0.07	0.02	**0.17**	0.09	0.02
US	-0.02	0.12	**0.15**	0.08	-0.12	-0.08	-0.12	-0.10
$\ell = 3$								
Germany	-0.23	0.34	**0.34**	0.07	-0.35	-0.48	-0.52	-0.34
France	0.18	-0.07	-0.06	0.08	**0.43**	0.23	0.41	0.42
Italy	-0.01	-0.37	-0.36	**0.21**	0.12	0.19	0.14	0.12
Japan	0.13	-0.06	-0.03	0.03	0.37	0.30	0.37	**0.37**
UK	-0.04	-0.08	-0.03	-0.10	0.07	**0.08**	0.07	0.06
US	-0.05	0.07	**0.08**	-0.02	-0.13	-0.13	-0.14	-0.12
$\ell = 4$								
Germany	-0.30	0.34	**0.35**	-0.06	-0.31	-0.52	-0.52	-0.29
France	0.31	-0.09	-0.09	0.29	**0.36**	0.14	0.29	0.36
Italy	-0.02	-0.41	-0.41	**0.26**	0.00	0.12	0.02	-0.01
Japan	0.12	-0.04	-0.02	-0.00	0.29	0.15	0.28	**0.29**
UK	-0.03	-0.21	-0.17	-0.11	-0.01	**0.03**	0.00	-0.01
US	-0.06	**0.04**	0.04	-0.14	-0.17	-0.15	-0.18	-0.16

Table 5.3: Cell entries denote correlations between IU measures introduced in (2) to (8) and IU as implied by the forecasts of experts surveyed by the ZEW ($u_{\tau+4|\tau}$).

The table entries indicate that in most economies, model- and survey based expressions of IU are positively associated. The dynamic and the dispersion based IU statistics seem to provide rather distinct sorts of information. Respective linkages to the benchmark do not show a strong common pattern. The correlations of distinct disparity measures with the survey based IU quantification are largely similar in magnitude. The same holds for the dynamic IU metrics $\hat{\sigma}_{\tau+\ell|\tau}$ and $h^{(\xi)}_{\tau+1|\tau}$. A stronger association is found between the survey measure and the model based dispersion statistics. Hence, we find that the dispersion measures are related to both benchmark approaches of IU measurement in a more pronounced way than the dynamic IU metrics. Lahiri and Sheng (2010) or Chua et al. (2011) report correlation statistics for the US, where long samples of survey expectation data are available. They examine the relation between IU quantifications based on survey data and those determined e.g. from GARCH models. Depending on the sample period and the anticipation horizon, correlations range from small negative up to magnitudes of to 0.9. Similarly, Zarnowitz and Lambros (1987) report correlations between survey based representations of $\hat{s}_{\tau+\ell|\tau}$ and $\bar{\sigma}_{\tau+\ell|\tau}$, which vary between -0.29 and 0.74 for distinct forecast horizons. Boero et al. (2008) find that the correlations between distinct survey based IU measures such as disagreement and an average uncertainty measure similar to $\bar{\sigma}_{\tau+\ell|\tau}$ amount to values of -0.11 to 0.03. Boero et al. (2008), however, find correlations of up to 0.68 once the influence of distinct forecast horizons is taken into account by means of regression models. We complement the correlation analysis by a graphical impression of IU over time. Distinct IU series are plotted as the median across economies. For all IU measures, a large reduction of uncertainty is indicated before the beginning of the financial crisis in its most severe form in 2008. This development parallels the reduction and stabilisation of international inflation dynamics known as the Great Moderation (Benati 2008). After 2008, however, the dynamic IU quantifications differ markedly from those of the disparity statistics. The uprise of IU after 2008 as indicated by the dynamic IU measures exceeds the initially high IU levels before the year 1990. Except $\bar{\sigma}_{\tau+\ell|\tau}$, the disparity statistics indicate an almost equal or even reduced level of IU relative to the years before 2008. This is also reflected in the trajectory of the benchmark IU measure $u_{\tau+4|\tau}$. The statistic $u_{\tau+4|\tau}$ shows an uprise of IU in the years 2008 and 2009. However, the overall level of IU as indicated by this measure has been relatively high before the financial crisis. This underscores the assertion of Lahiri and Liu (2005) on the difficulty to determine the appropriate IU measure during turbulent times. The preliminary data analysis in this chapter suggests that the problem of selecting an IU measure might amount to the choice between a dynamic and a dispersion statistic. Differences among the candidate measures from one of these groups appear less pronounced. To compare the relative merits of dynamic and dispersion IU metrics, we next devise an out-of-sample forecasting study.

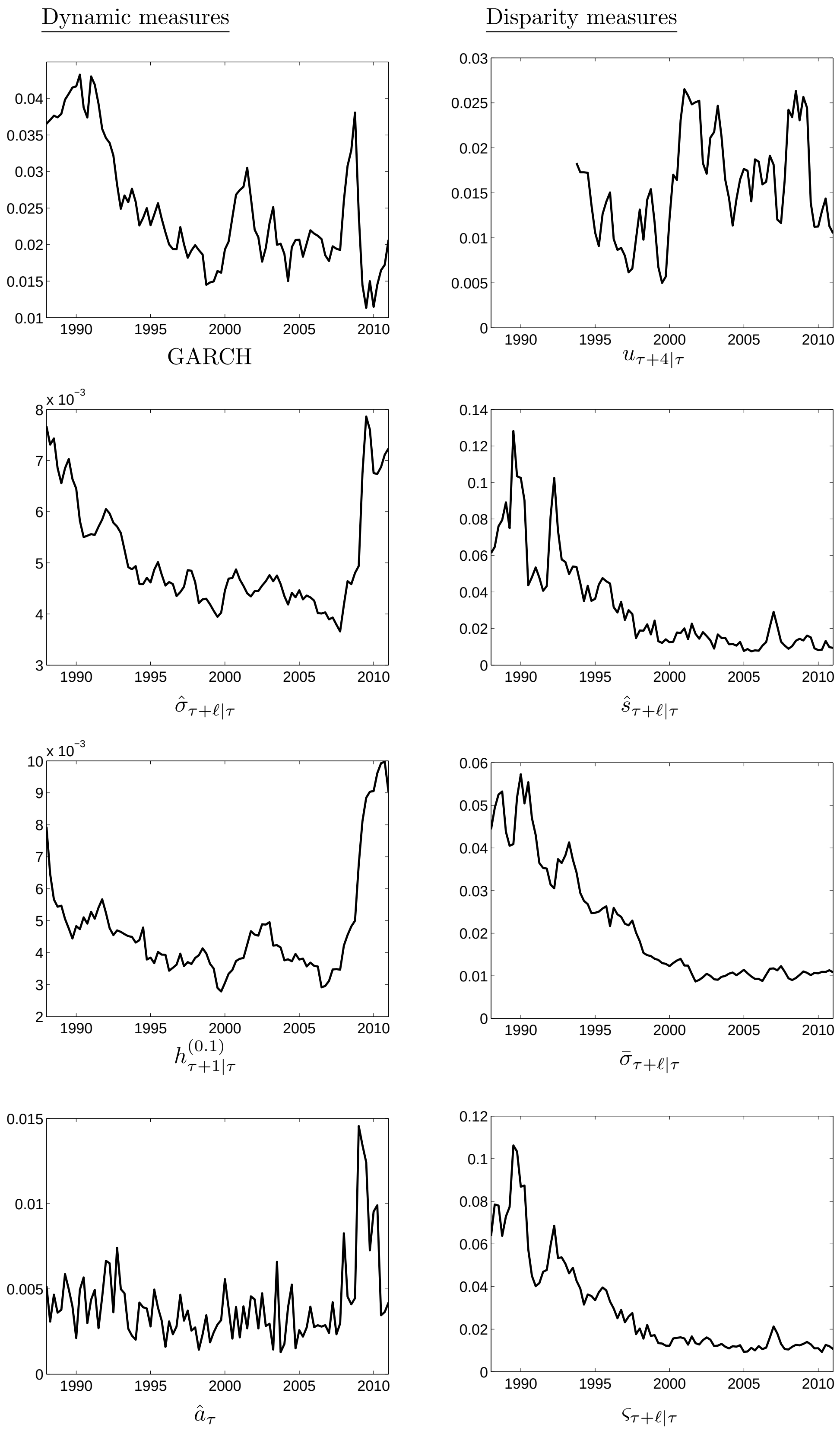


Fig. 5.2: Median IU across economies for $\ell = 1$.

6. INFLATION UNCERTAINTY AS AN INDICATOR OF BOND YIELDS

6.1 Outline

The two most prominent families of IU approximations are time series based approaches like conditionally autoregressive heteroscedastic (GARCH, Engle 1982, Bollerslev 1986) processes and its descendants, and dispersion measures of forecast surveys (Lahiri and Sheng 2010). A widely used representative of the latter approach is the standard deviation of expert forecasts. Either of the two approaches relies on distinct sources of information. They also process information in different ways (Batchelor and Dua 1996, Mankiw and Reis 2004). Therefore, time series and survey based methods might provide diverging estimates of IU in many situations. Lahiri and Liu (2005) find that such distinct IU indications deviate most during turbulent times, e.g. in the case of the US after the first oil price shock. This means that choosing among distinct IU measures is particularly difficult in circumstances of highest relevance. The problem to choose from a set of potential IU measures has been recognised since several years. At least two distinct ways to single out an empirical IU measure have emerged. Firstly, compliance with an economic definition of uncertainty may be a necessary condition of a meaningful IU approximation. For example, Giordani and Söderlind (2003) or Rich and Tracy (2003) point out that GARCH models do not express IU from an ex-ante point of view. Therefore they argue that measures based on forecast surveys are preferable to GARCH-based measures. Similarly, Lahiri and Sheng (2010) and Chua et al. (2011) assess several distinct expressions of IU by means of their relation to a survey based benchmark measure. Another objection to the GARCH model class is that these specifications have been mainly derived to fit stylised facts like volatility clustering in inflation data. Goodness-of-fit, however, may not be a sufficient criterion to evaluate IU measures, especially if the aim is to formulate an economic interpretation of IU (Peng and Yang 2008). A second way to select IU measures is to rely on statistical arguments. For example, Lahiri and Liu (2005) show that the standard deviation of expert forecasts can be a biased measure of IU. For this reason, they propose to combine this measure with the average over individual experts' IU quantifications.

In the following, we propose an alternative way to evaluate IU measures. In several studies, the Fisher equation is augmented by means of an IU term (Blejer and Eden 1979, Levi and Makin 1979). We draw upon this relation to rank IU measures according to their marginal predictive content. Forecasting proceeds in the framework of a Bayesian model averaging (BMA) approach. In this way, predictions based on alternative model specification choices are combined by means of exact posterior probability weights. Among distinct means of model selection or -combination, such methods have been documented to yield particularly high predictive accuracy (Koop and Potter 2003, Wright 2008). Along these lines, we investigate the scope of IU measures to predict yields on long term government bonds. We focus on these securities because of their prominent role in the current debate on the sustainability of sovereign debt. Moreover, the risk to incur losses due to inflation is largest for debt obligations with long maturities. Missale and Blanchard (1994) argue that short-term debt obligations might be regarded as broadly equivalent to inflation-indexed bonds. In the related literature, the concept of IU largely refers to the risk of welfare losses from surprises in future inflation. Therefore, it seems sensible to compare IU measures by means of ex-ante forecasting.

Barnea et al. (1979) or Friedman (1977) assert that IU influences anticipated returns on both financial or tangible assets. Brenner and Landskroner (1983) describe how IU affects bond returns in the form of an inflation risk premium. In general, investment and savings decisions require the consideration of intertemporal tradeoffs with regard to streams of nominal income. The ex-ante predictive content of IU measures might be important for consumers, investors and also for the conduct of monetary policy (Friedman 1977; Barnea et al. 1979; Brenner and Landskroner 1983). However, several theories disagree on whether the IU influence on interest rates is positive or negative (Lahiri et al. 1988). Therefore, in addition to the forecast evaluation, we examine the direction of this effect.

6.2 Model framework

In this section, the methodology to evaluate alternative IU measures is described. After recalling theoretical assertions on the economic relevance of IU, we extend the Fisher equation by incorporating candidate IU measures one after the other. In this way, we assess their relative predictive content. We proceed with a description of the data set. After discussing statistical properties of distinct IU measures, the forecasting methodology is introduced.

6.2.1 The augmented Fisher equation

To assess the strength and the direction of the IU impact on interest rates, we determine ℓ-periods-ahead predictions of interest rates, denoted $\hat{R}_{\tau+\ell|\tau}$, by means of an autoregressive distributed lag (ADL) model. The ADL scheme reads as

$$R_{\tau+\ell} = \gamma_{10} + \gamma_{11}\tau + \gamma_{12}(L)\pi_\tau + \gamma_{13}(L)R_\tau + \gamma_{14}(L)IU_{\tau+\ell|\tau} + e_{\tau+\ell}, \quad (6.1)$$

with $\tau = T_0^* - \ell, ..., T^* - \ell$ and where, e.g., $\gamma_{12}(L) = \gamma_{12,0} + \gamma_{12,1}L + \cdots + \gamma_{12,P}L^P$. In (6.1), L denotes the lag operator, i.e. $L^p\pi_\tau = \pi_{\tau-p}$, the term $IU_{\tau+\ell|\tau}$ represents a particular inflation uncertainty measure and $e_{\tau+\ell} \overset{iid}{\sim} (0, \sigma_e^2)$. The formulation in (6.1) largely corresponds to the 'augmented Fisher relation' in Blejer and Eden (1979) or Levi and Makin (1979). Based on this model, the value of distinct IU measures is assessed by means of their potential to improve predictions of $R_{\tau+\ell}$. Furthermore, the overall impact of IU on $R_{\tau+\ell}$, $\bar{\gamma}^{(IU)} = \gamma_{14}(1)$, indicates if $IU_{\tau+\ell|\tau}$ might be interpreted as a risk premium or as an impediment to aggregate investment.

6.2.2 The forecasting design

The comparative forecast evaluation of distinct IU measures proceeds by means of pseudo out-of-sample cross validation. Similar to cross-validation (CV) techniques, each observation $R_{\tau+\ell}$ from the considered period $\tau = T_0^* - \ell, ..., T^* - \ell$ is predicted ℓ-steps ahead by means of a respective leave-one-out estimate. The computation of ℓ-steps-ahead predictions is straightforward due to the linear relation between $R_{\tau+\ell}$ and the explanatory variables which are conditional on information up to period τ (Chevillon 2005). In this chapter, the time instances $T_0^* - \ell$ and $T^* - \ell$ correspond to 1988Q1 and 2011Q1, respectively. To capture the dynamics in seasonally adjusted quarterly data, each lag polynomial of the predictor variables π_τ, R_τ and $IU_{\tau+\ell|\tau}$ in (6.1) comprises at most 4 terms (i.e. $P = 3$). Therefore, distinct subset modelling choices give rise to a total of $M = 2^{12}$ alternative specifications of the Fisher equation[1]. Relying on the scope of forecast combinations to improve predictive accuracy (Raftery et al. 1997), we consider all $m = 1, ..., M$ subset models and subsequently combine the corresponding forecasts by means of Bayesian model averaging

[1] Choosing a higher maximal lag order like e.g. $P = 4$ obtains qualitatively equivalent outcomes in the forecast comparison study. These results which are available from the authors upon request.

(BMA). The following exposition of a feasible BMA procedure which relies on exact posterior probabilities follows Wasserman (2000). Combined predictions obtain as

$$\hat{R}_{\mathcal{T}+\ell|\mathcal{T}} = \sum_{m=1}^{M} \theta_m^* \hat{R}^{(m)}_{\mathcal{T}+\ell|\mathcal{T}}, \tag{6.2}$$

with

$$\theta_m^* = \frac{\theta_m}{\sum_m \theta_m} \text{ and } \theta_m = \int L_m(\boldsymbol{\gamma}^{(m)}) p_m(\boldsymbol{\gamma}^{(m)}) d\boldsymbol{\gamma}^{(m)}. \tag{6.3}$$

In (6.3), $L_m(\boldsymbol{\gamma}^{(m)})$ and $p_m(\boldsymbol{\gamma}^{(m)})$ represent the likelihood and the a-priori distribution regarding the parameters $\boldsymbol{\gamma}^{(m)}$ from $m = 1, ..., M$ reformulations of (6.1), respectively. Based on the log-likelihood function $l(\boldsymbol{\gamma}^{(m)}) = \ln L(\boldsymbol{\gamma}^{(m)})$, exact posterior probabilities θ_m in (6.3) can be approximated as

$$\ln \hat{\theta}_m = l(\hat{\boldsymbol{\gamma}}^{(m)}) - \frac{n_m}{2} \ln(\mathcal{T}), \tag{6.4}$$

where $\hat{\boldsymbol{\gamma}}^{(m)}$ denotes the (Q)ML estimator of $\boldsymbol{\gamma}^{(m)}$, and n_m stands for the number of right hand side variables in model m. The number of observations for leave-one-out estimation is $\mathcal{T} = T^* - T_0^*$. A feasible rule to compute forecast combination weights[2] is to replace θ_m in (6.3) by $\exp\Big(l(\hat{\boldsymbol{\gamma}}^{(m)}) - \frac{n_m}{2}\ln(\mathcal{T})\Big)$.

6.2.3 *The ranking of forecasts*

Next, we describe the methodology to obtain a ranking of IU measures. After a description of the performance criterion, some additional means to quantify IU are introduced.

[2] For horizons $\ell > 1$, the weights θ_m^* in (6.3) might not be strictly suitable because of potential serial correlation in the forecast errors, and thus, misspecification of the likelihood function (Wright 2008). Forecasting results for combined ℓ-step-ahead predictions which are drawn from likelihood estimates determined under $\ell = 1$ leaves the outcomes of the forecasting study essentially unaffected. These results are available from the authors upon request.

Performance criterion

A ranking of IU measures is constructed by means of mutual comparisons of absolute forecast errors (AE) which are given by

$$|e^{\bullet}_{i,\tau+\ell|\tau}| = |\hat{R}^{\bullet}_{i,\tau+\ell|\tau} - R_{\tau+\ell}| \tag{6.5}$$

for economies $i = 1, ..., 18$. In (6.5), '$\bullet$' indicates that forecasts are obtained for distinct IU measures, i.e. $\bullet \in \{\hat{\sigma}_{\tau+\ell|\tau}, h^{(\xi)}_{\tau+1|\tau}, \hat{a}_{\tau}, \hat{s}_{\tau+\ell|\tau}, \bar{\sigma}_{\tau+\ell|\tau}, \varsigma_{\tau+\ell|\tau}, \zeta_{\tau+\ell|\tau},$ $\max(\text{IU}), \min(\text{IU}), \text{median}(\text{IU}), \overline{TS}, \overline{DS}\}$. Following Stock and Watson (1999), we compare alternative predictions by means of the criterion

$$\text{TOP3}^{\bullet} = (1/((T^* - T_0^* + 1) \times 18)) \sum_{\tau=T_0^*-\ell}^{T^*-\ell} \sum_{i=1}^{18} \text{I}(|e^{\bullet}_{i,\tau+\ell}| \le |e^{(3)}_{i,\tau+\ell}|), \tag{6.6}$$

where $\text{I}(\cdot)$ is an indicator function and $|e^{(3)}_{i,\tau+\ell}|$ denotes the 3rd-smallest absolute prediction error. In addition to the $\text{TOP3}^{\bullet}$ frequency, we report frequencies of $(T - T_0 + 1) \times 18$ cases where $|e^{\bullet}_{i,\tau+\ell}| \le |e^{(bm)}_{i,\tau+\ell}|$. We let $|e^{(bm)}_{i,\tau+\ell}|$ denote an AE either from (6.1) presuming that IU does not exert an effect on interest rates, i.e. $\gamma^{(IU)} = 0$ or by augmenting (6.1) with one of the benchmark IU measures GARCH and $u_{\tau+4|\tau}$.

Aggregate and benchmark measures of IU

The dispersion IU measures (5.6) to (5.8) are determined as averages of other IU statistics. The construction of these IU metrics is motivated in section 2 and, e.g., in the studies of Wallis (2005) and Lahiri and Sheng (2010). Additionally, we introduce several IU measures which are determined as the maximum, the minimum and the median of the IU metrics (5.2) to (5.8). Moreover, we consider the average over the time-series IU metrics on the one hand and the disparity IU measures on the other hand as further IU quantifications, denoted $\overline{TS}$ and $\overline{DS}$, respectively. These additional IU quantifications may reveal if the forecasting content of individual measures can be fruitfully combined. Finally, model based IU metrics are compared with the GARCH(1,1) and the $u_{\tau+4|\tau}$ benchmark measures introduced in section 4.2 for anticipation horizons $\ell = 1$ and $\ell = 4$, respectively.

Assessing predictive accuracy in subsamples

It seems unlikely that the predictive content provided by individual IU measures remains largely equivalent for distinct times or across economies (Lahiri and Liu 2005). The display of the IU trajectories in figure 5.2 shows that dynamic and dispersion measures obtain particularly distinct IU quantifications after 2008. During turbulent times, it is also most likely that economic decisions are affected by the uncertainty about future inflation. Thus, we compare separate frequencies of TOP3$^{\bullet}$ for either calm or more turbulent subperiods. We distinguish between calm and turbulent periods by means of the standard deviation over the IU metrics in (5.2) to (5.8) at each forecasting step $\tau = T_0^* - \ell, ..., T^* - \ell$, denoted as $SD_{\tau+\ell|\tau}$. Conditional forecast rankings are determined by computing the average TOP3$^{\bullet}$ measure separately for all sample observations above and below the median of $SD_{\tau+\ell|\tau}$. Moreover, we distinguish performance rankings between earlier and later periods of the estimation sample by splitting the available time instances into two periods of equal length. This may reveal if certain IU statistics have become more relevant for interest rate forecasting in the course of the two recent decades. Furthermore, the explanatory content of distinct IU measures might depend on historical experiences of distinct economies with respect to inflation rates (Clarida and Gertler 1997). We therefore evaluate the candidate IU measures separately for nine higher-inflation and nine lower-inflation economies.

6.3 Results

After a brief overview of the literature on IU as an explanatory variable, this section summarises and interprets the results of the forecast comparison. Subsequently, we examine distinct interpretations of the influence of IU on interest rates.

6.3.1 Uncertainty as predictor in the empirical literature

The literature on forecasting interest rates and other macroeconomic variables documents that uncertainty measures can be useful predictors in many situations. Hong et al. (2004) provide evidence for a significant impact of GARCH-implied uncertainty terms on density forecasts of 1-month US T-bill rates in an out-of-sample study. Höhrdahl et al. (2006) compare the out-of-sample forecast accuracy of term structure models to the performance of univariate models. They find that term structure models which incorporate distinct inflation risk measures outperform specifications like the random walk. Moreover, Kurz and Motolese (2011) find that the disagreement of market analysts' predictions is positively associated with risk premia of stock returns. In contrast, Elliot and Ito (1999) find that the disagreement among expert forecasts of the Yen/Dollar spot FX rate is not significantly related to the realised profits from distinct trading rules.

6.3.2 Forecasting interest rates

Table 6.1 reports the TOP3$^{\bullet}$ frequencies of alternative IU measures. The disparity measure $\bar{\sigma}_{\tau+\ell|\tau}$ obtains as the most informative predictor. The ranking is particularly clear-cut for anticipation horizons $\ell > 1$. Other IU statistics from the dispersion class contribute less to the forecasting accuracy of the augmented Fisher relation. From the set of time-series statistics, the measure

$\hat{\sigma}_{\tau+\ell|\tau}$ is relatively frequently among the best candidates. Summary measures of IU like, for example, the median over all IU metrics or the mean of the dynamic IU statistics also take up high ranks in some cases, e.g. for $\ell = 1$. On average across horizons, however, these statistics lead to less accurate forecasts than $\bar{\sigma}_{\tau+\ell|\tau}$. The relatively high TOP3$^{\bullet}$ frequencies of $\overline{TS}$ suggest that forecast precision is likely to improve if distinct time-series measures are combined. This does not apply to a similar extent for the dispersion measures. Moreover, similar to Lahiri and Sheng (2010), we find that the distinction between $\hat{s}_{\tau+\ell|\tau}$ and $\bar{\sigma}_{\tau+\ell|\tau}$ increases with ℓ.

Table 6.1: TOP3$^{\bullet}$

	Dynamic measures					Dispersion measures			
	$\ell = 1$	$\ell = 2$	$\ell = 3$	$\ell = 4$		$\ell = 1$	$\ell = 2$	$\ell = 3$	$\ell = 4$
$\hat{\sigma}_{\tau+\ell\|\tau}$	21.45	24.16	25.32	25.19	$\hat{s}_{\tau+\ell\|\tau}$	21.51	20.09	20.54	20.74
$h^{(0.1)}_{\tau+1\|\tau}$	23.32	22.03	21.77	21.77	$\bar{\sigma}_{\tau+\ell\|\tau}$	22.35	**27.65**	**28.62**	**27.97**
$h^{(0.2)}_{\tau+1\|\tau}$	23.26	21.77	17.57	18.09	$\varsigma_{\tau+\ell\|\tau}$	15.96	18.15	20.80	21.90
$\hat{a}_{\tau}$	26.94	23.06	22.93	23.13	$\zeta_{\tau+\ell\|\tau}$	19.44	20.22	22.22	20.93
$\overline{TS}$	**28.81**	24.22	21.38	20.99	$\overline{DS}$	19.06	18.28	18.99	21.12
	Further IU statistics								
max(IU)	15.70	16.86	20.80	20.09	median	20.74	23.00	22.48	23.39
min(IU)	19.51	21.83	20.16	17.12	w/o IU	22.16	19.51	18.22	19.32

Cell entries represent the frequencies in which distinct IU measures lead to forecasts which are among the 3 most accurate predictions. The row labelled as 'w/o IU' reports respective frequencies for a forecasting model without an IU term. Highest frequencies among distinct IU measures appear in boldface.

Table 6.2 reports how often distinct IU measures improve upon forecasts from (6.1) without IU terms. The absolute forecast errors obtained for the latter case are denoted as $|e^{(\circ)}_{\tau+\ell|\tau}|$. The left panel shows that it is generally beneficial to predict interest rates by consideration of IU, since the frequencies almost uniformly exceed 50%. In the right panel, the absolute errors $|e^{(\circ)}_{\tau+\ell|\tau}|$ are scaled downwards by $c = 0.8$ to enable more clear-cut distinctions. Apparently, the $\bar{\sigma}_{\tau+\ell|\tau}$ IU measure is the best performing candidate IU statistic also in this respect.

Table 6.2: Percentage of cases where $|e^{\bullet}_{\tau+\ell|\tau}| < c \times |e^{(\circ)}_{\tau+\ell|\tau}|$

	$c=1$				$c=0.8$			
	$\ell=1$	$\ell=2$	$\ell=3$	$\ell=4$	$\ell=1$	$\ell=2$	$\ell=3$	$\ell=4$
$\hat{\sigma}_{\tau+\ell\|\tau}$	51.03	53.29	55.49	54.84	22.22	29.07	30.75	31.20
$h^{(0.1)}_{\tau+1\|\tau}$	**51.87**	54.20	52.71	52.00	18.09	21.25	21.25	19.77
$h^{(0.2)}_{\tau+1\|\tau}$	51.74	53.94	52.84	51.74	15.50	17.64	17.70	15.31
$\hat{a}_{\tau}$	49.55	51.16	52.78	52.78	26.94	29.13	28.94	28.10
$\hat{s}_{\tau+\ell\|\tau}$	51.42	53.55	54.97	54.97	26.49	31.65	35.79	34.82
$\bar{\sigma}_{\tau+\ell\|\tau}$	49.68	53.04	53.29	55.10	22.87	**34.04**	35.34	**36.82**
$\varsigma_{\tau+\ell\|\tau}$	50.19	53.10	56.07	55.56	25.32	31.65	35.47	35.92
$\zeta_{\tau+\ell\|\tau}$	50.45	52.71	54.91	54.72	**27.45**	33.01	**37.34**	35.21
max(IU)	50.45	53.10	**56.20**	55.62	25.26	32.11	35.47	35.59
min(IU)	49.94	53.62	52.97	50.97	18.80	22.42	22.80	22.87
median(IU)	51.55	**55.88**	52.26	55.62	21.45	30.62	30.30	34.30
$\overline{TS}$	51.16	51.36	52.39	53.23	26.94	28.42	28.55	27.78
$\overline{DS}$	50.65	53.23	56.14	**55.62**	25.97	31.91	35.85	35.79

The symbol '$\circ$' represents forecast errors obtained from (9) presuming $\gamma_{14,p} = 0\ \forall p$. In the right part of the table, $|e^{(\circ)}_{\tau+\ell|\tau}|$ is scaled downwards to obtain more pronounced distinctions among alternative IU measures.

The comparisons of dynamic and dispersion IU measures to GARCH-implied IU and the survey based measure $u_{\tau+4|\tau}$ from (5.9) as benchmarks are shown in table 6.3.

Table 6.3: Percentage of cases where $|e^{\bullet}_{\tau+\ell|\tau}| < |e^{(bm)}_{\tau+\ell|\tau}|$

$\hat{\sigma}_{\tau+1\|\tau}$	$h^{(0.1)}_{\tau+1\|\tau}$	$h^{(0.2)}_{\tau+1\|\tau}$	$\hat{a}_{\tau}$	$\hat{s}_{\tau+1\|\tau}$	$\bar{\sigma}_{\tau+1\|\tau}$	$\varsigma_{\tau+1\|\tau}$	$\zeta_{\tau+1\|\tau}$
52.97	52.58	**54.13**	50.06	52.00	52.07	52.45	51.94
$\hat{\sigma}_{\tau+4\|\tau}$	$h^{(0.1)}_{\tau+1\|\tau}$	$h^{(0.2)}_{\tau+1\|\tau}$	$\hat{a}_{\tau}$	$\hat{s}_{\tau+4\|\tau}$	$\bar{\sigma}_{\tau+4\|\tau}$	$\varsigma_{\tau+4\|\tau}$	$\zeta_{\tau+4\|\tau}$
52.65	52.78	47.62	48.94	52.91	52.53	**56.61**	53.70

The upper part of the table reports outcomes for comparisons with GARCH(1,1) as the benchmark (bm) measure at $\ell = 1$. In the lower part of the table, $\ell = 4$ and bm corresponds to the survey statistic $u_{\tau+4|\tau}$. Comparisons with $u_{\tau+4|\tau}$ are limited to a cross section of six economies as listed in section 4.2 and the time period between 1992Q2 and 2011Q1. Predictions based on the IU metrics max(IU), min(IU), median(IU), $\overline{TS}$ and $\overline{DS}$ are omitted for space considerations.

Both groups of IU metrics turn out to be more valuable predictors than either benchmark measure. Predictions based on model-implied IU metrics outperform the benchmark IU statistics in more than 50% of all instances. These findings underscore that model based IU metrics are sensible representatives of the two distinct families of IU measures. Sample-specific rankings are reported in table 6.4. To economise on space, we report only comparisons between the 3 most successful candidate IU metrics. In general, the lead of $\bar{\sigma}_{\tau+\ell|\tau}$ over other IU measures is strongest at higher forecast horizons. In particular, a large predictive contribution of this IU measure is found for turbulent periods. During such times, the identification of the most appropriate IU statistic might be especially important. Dividing the sample into early and recent observations further reinstates the findings regarding the robust performance of $\bar{\sigma}_{\tau+\ell|\tau}$. We find that the importance of $\bar{\sigma}_{\tau+\ell|\tau}$ has been increasing during the recent two decades. While the performance numbers of $\bar{\sigma}_{\tau+\ell|\tau}$ are not largely different from those of $\hat{\sigma}_{\tau+\ell|\tau}$ until 1998, the distinction becomes rather clear during subsequent years until 2011. Furthermore, table 6.4 shows separate results for low- and high inflation economies. The ranking of IU measures is more pronounced for economies with higher average inflation rates. This might be due to the well-documented positive association between the level and the uncertainty of inflation (Friedman 1977, Ball 1992, Hartmann and Herwartz 2012). The explicit consideration of uncertain periods appears to be a suitable means to obtain clear-cut distinctions among measures of IU. This is in line with the findings of Lahiri and Liu (2005). Our results suggest that the $\bar{\sigma}_{\tau+\ell|\tau}$ IU measure is particularly useful during such situations, when the measurement of IU might be of highest relevance for economic decision takers.

Table 6.4: TOP3$^{\bullet}$, results for subsamples

	$\ell=1$	$\ell=2$	$\ell=3$	$\ell=4$	$\ell=1$	$\ell=2$	$\ell=3$	$\ell=4$
	Turbulent periods				Calm periods			
$\hat{\sigma}_{\tau+\ell\vert\tau}$	19.64	23.39	22.61	24.55	23.26	24.94	28.04	25.80
$\hat{a}_{\tau}$	**26.23**	23.00	21.19	20.93	**27.24**	23.13	24.68	25.32
$\bar{\sigma}_{\tau+\ell\vert\tau}$	22.61	**27.91**	**28.29**	**27.00**	22.09	**27.39**	**28.94**	**28.94**
	Sample period 1988Q1-1998Q3				Sample period 1998Q4-2011Q1			
$\hat{\sigma}_{\tau+\ell\vert\tau}$	21.71	24.68	27.00	26.61	21.19	23.64	23.64	23.77
$\hat{a}_{\tau}$	**29.36**	23.51	23.64	21.83	**25.19**	22.61	22.22	24.42
$\bar{\sigma}_{\tau+\ell\vert\tau}$	20.67	**26.61**	**27.91**	**27.26**	24.03	**28.37**	**29.33**	**28.68**
	Higher-inflation economies				Lower-inflation economies			
$\hat{\sigma}_{\tau+\ell\vert\tau}$	19.38	22.48	24.94	22.74	23.51	25.84	25.71	27.43
$\hat{a}_{\tau}$	**25.19**	21.06	19.12	19.64	**28.68**	25.06	26.74	26.61
$\bar{\sigma}_{\tau+\ell\vert\tau}$	20.93	**27.15**	**29.33**	**28.29**	23.77	**27.11**	**27.91**	**27.65**

Turbulent and calm periods are distinguished according to whether the standard deviation over the IU metrics in (2) to (8) exceeds its median value. Similarly, the cross section of 18 economies is split into 2 groups labelled 'Higher-' and 'Lower-inflation' according to their average inflation rate over the sample period. For further descriptions see table 6.1.

6.3.3 The effect of IU on interest rates

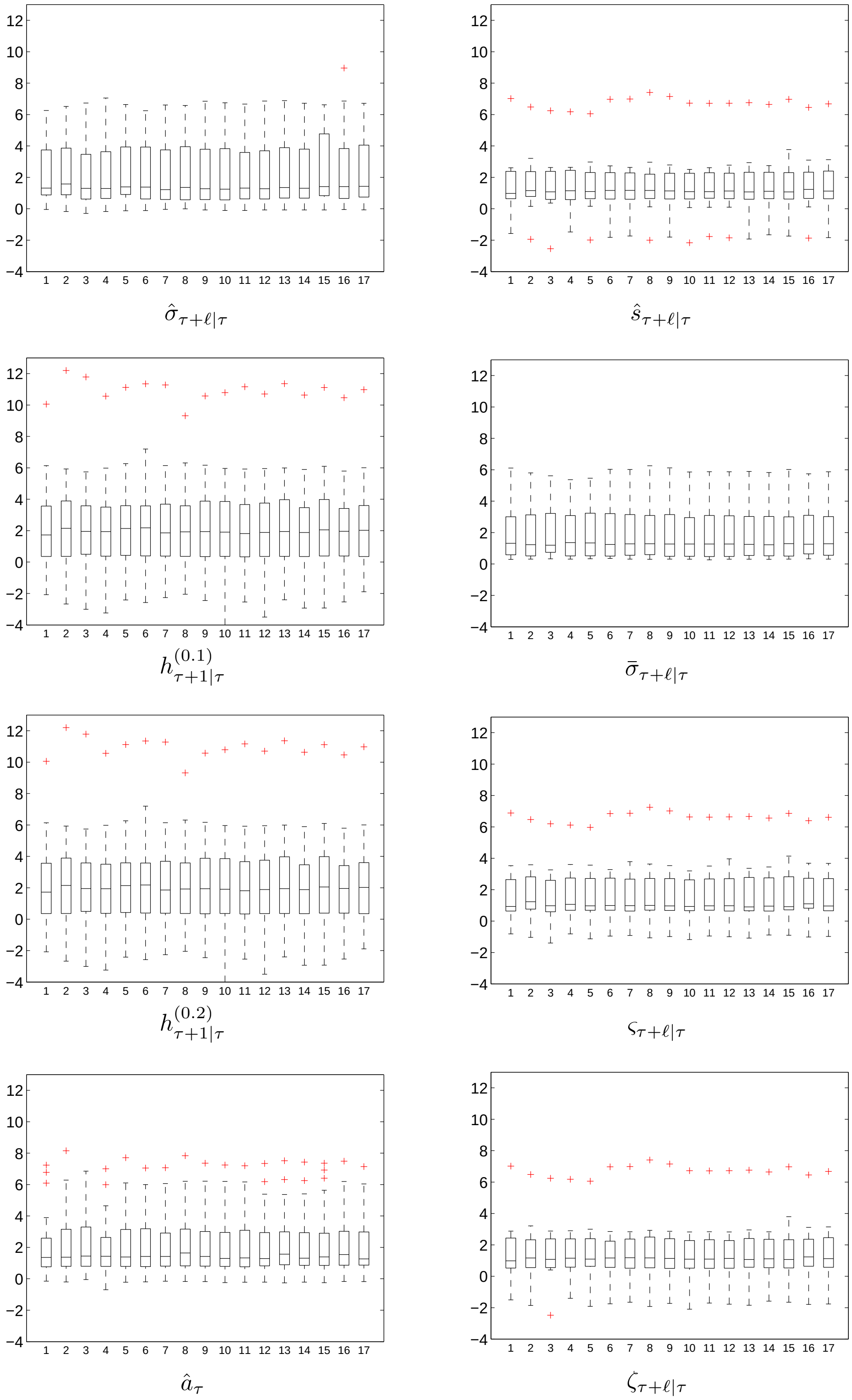
Theoretical explanations of the IU influence assert that both the demand for loanable funds from investors and the supply of savings tend to be discouraged by higher IU (Lahiri et al. 1988). This means that, ceteris paribus, the sign of the respective IU impact on interest rates will be negative if the former effect dominates and positive in the contrary case. Hence, coefficient estimates from (6.1) provide evidence on which influence is the prevailing one. Figure 6.1 contains boxplots of the accumulated IU effect on interest rates $\bar{\hat{\gamma}}_{i\tau}^{(IU)}$ based on estimation steps $\tau = T_0^*, ..., T^*$ of the CV subsampling scheme and economies $i = 1, ..., 18$. The estimated influence of IU on interest rates is positive for most economies. This means that the inflation risk premium required to supply savings impacts on interest rates more strongly than firms' demand for investment capital. However, most IU metrics yield estimates which are negative for several economies. Such cases do not permit a straightforward interpretation of the IU effect. In contrast, the measures $\bar{\sigma}_{\tau+\ell|\tau}$, $\hat{\sigma}_{\tau+\ell|\tau}$ and $\hat{a}_{\tau}$

obtain estimates which are almost uniformly positive. Interestingly, these are also the most successful candidate IU measures in the forecast competition. This suggests that the interpretation of the IU influence on interest rates as a risk premium is the more relevant explanation.

6.4 Summary

We assess forecasts of government bond interest rates, processing alternative inflation uncertainty measures as predictor variables. In the related literature, two categories of inflation uncertainty metrics are distinguished. The first group are time-series measures, the other one is based on the heterogeneity of individual inflation forecasts. The forecast competition shows that the average over individual uncertainties as a representative of the dispersion family is the most viable predictor variable for interest rates. We further note that all uncertainty measures uniformly indicate a decrease in inflation uncertainty during the years of the so-called Great Moderation. While time-series measures indicate a considerable uprise of inflation risk after 2008, the dispersion measures still indicate a moderate increase in inflation uncertainty. For the measures with highest predictive content, estimates of the relation between inflation uncertainty and interest rates are uniformly positive across economies.

Fig. 6.1: The overall impact of IU on interest rates



Estimates $\bar{\hat{\gamma}}^{(IU)}_{i\tau}$, $\tau = T_0^*, ..., T^*$ from (6.1), for distinct IU measures are depicted as averages over 17 equally-sized subperiods of the sample period 1988Q1 to 2011Q1. Each observation corresponds to a subwindow-specific average IU effect in economy i. Since the sample period covers 86 observations in total, the first average IU effect is based on 6 observations.

7. CAUSALITY BETWEEN INFLATION AND INFLATION UNCERTAINTY

7.1 Outline

Decisions about the priority of either targeting the level of inflation or stabilising monetary policy require knowledge about the linkage between inflation and its associated uncertainty. Friedman (1977) and Ball (1992) argue for causality pointing from inflation to inflation uncertainty (IU), whereas in several other contributions, the opposite causal relationship is postulated (Davis and Kanago 2000 provide a literature review). Empirical studies find evidence for both the Friedman-Ball suggestion (FB) and the opposite causal direction (CM, cf. Cukierman and Meltzer 1986). In chapter 4, inferential results on the causal impact of IU on inflation are documented in the framework of a GARCH model. In the following, both the CM and the FB assertion are examined by means of the ex-ante IU measures (5.2), (5.4) and (5.6). Causality is assessed from both an in-sample (IS) and an out-of-sample (OS) perspective. Similar to the investigation in chapter 4, we evaluate the cross-sectional robustness of inferential conclusions. Empirical results are based on the $\mathcal{M}22$ dataset. In contrast to the GARCH-based inference, we address the possibility of structural change by means of splitting the sample period into subperiods that might correspond to distinct policy regimes. Thereby we limit the risk of drawing biased conclusions as a result of smoothing over largely distinct regimes in the inflation and IU process. Subsequently, the IS and OS approach to causality testing are described.

7.2 Model framework

In this Section, the IS and OS testing schemes are introduced first. A discussion of results follows.

7.2.1 In-sample schemes

We estimate a sequence of $k = 1, ..., K$ bivariate SUR regressions

$$\begin{pmatrix} IU_{i\tau} \\ \pi_{i\tau} \end{pmatrix} = \begin{pmatrix} \mu_{i1,\tau-1} \\ \mu_{i2,\tau-1} \end{pmatrix} + \sum_{p=1}^{P} \underbrace{\begin{bmatrix} \gamma_{11,ip} & \gamma_{12,ip} \\ \gamma_{21,ip} & \gamma_{22,ip} \end{bmatrix}}_{\Gamma_{ip}} \begin{pmatrix} IU_{i,\tau-p} \\ \pi_{i,\tau-p} \end{pmatrix} \tag{7.1}$$

$$+ \sum_{p=1}^{P} \Psi_{ip} \begin{pmatrix} y^{\bullet}_{i,\tau-p} \\ y^{\bullet}_{i,\tau-p} \end{pmatrix} + \begin{pmatrix} v_{i1\tau} \\ v_{i2\tau} \end{pmatrix}, \qquad \begin{matrix} i = 1, ..., 18, \\ \tau \in W_k, \end{matrix}$$

where $IU_{i\tau} \in \{\hat{\sigma}_{\tau+1|\tau}, \hat{a}_{\tau+1}, \bar{\sigma}_{\tau+1|t}\}$, $\mu_{ij,\tau-1} = \mu_{ij0} + \mu_{ij1}(\tau-1)$ covers deterministic patterns and $(v_{i1\tau}, v_{i2\tau})' \sim (0, \Omega_i)$. Allowing for potential structural change in the IU and inflation series, we partition the full sample period $[T_0^* + P_{\max} + 1, ..., T^*]$, $P_{\max} = 6$, into nonoverlapping segments W_k of equal size E_K. Sequential estimation[1] of (4) is conducted with given presample values such that each regression design comprises E_K observations. The number of subsamples is $K = \lfloor (T^* - T_0^* - P_{\max})/E_K \rfloor$. Alternative output measures are represented as $y^{\bullet}_{i,\tau-1} \in \{\tilde{y}^{HP}_{i,\tau-1}, \tilde{y}^{CF}_{i,\tau-1}, \Delta_{12} y_{i,\tau-1}\}$. Output gap estimation confines to observations from respective time segments to consequently allow for subperiod-specific inference. The parameter matrices Γ_{ip} and Ψ_{ip} capture influences of IU estimates, inflation and output statistics, respectively. Pre-

[1] To improve numerical accuracy, IU series are multiplied by 10 such that $IU_{i\tau}$ and $\pi_{i\tau}$ have approximately equivalent scales.

dictor selection is carried out by means of an initial regression and removal of regressors which are insignificant at the 5% critical level[2].

Five distinct, yet related null hypotheses of noncausality are examined, where the alternative hypothesis is throughout that both the FB and the CM assertion hold jointly, i.e. $H_1 : \ \gamma_{12,p} \neq 0$ and $\gamma_{21,p} \neq 0$ for at least one $p \in \{1, ..., P\}$ in (7.1). The most restrictive assertion of no causality in either direction is $H_0 : \ \gamma_{12,p} = \gamma_{21,p} = 0, \forall p$. Rejections of $H_{01} : \ \gamma_{12,p} = 0, \forall p$, or $H_{02} : \ \gamma_{21,p} = 0, \forall p$, are interpreted as causality in the FB or the CM sense, respectively. More concise policy recommendations may be obtained by testing FB and CM given an explicit statement about the opposite causal relation. To examine such cases we consider conditional hypotheses $H_{03} : \ \gamma_{12,p} = 0 \mid \gamma_{21,p} = 0, \forall p$, and $H_{04} : \ \gamma_{21,p} = 0 \mid \gamma_{12,p} = 0, \forall p$, where causality points in one specific direction. For instance, stronger evidence against H_{03} in comparison with H_{04} suggests that targeting the level of inflation is also beneficial for the stabilisation of inflation. An instance of conditional causality, i.e. rejection of H_{03} or H_{04}, is indicated whenever only one of the unconditional hypothesis H_{01} and H_{02} can be rejected. Hypotheses are tested by means of F-tests at the 5% significance level.

7.2.2 Out-of-sample schemes

Causality may also be detected with reference to forecasting ability. Within each subperiod, one-step predictions obtain as

$$\begin{pmatrix} I\hat{U}^{(\circ)}_{i,\tau+1|\tau} \\ \hat{\pi}^{(\circ)}_{i,\tau+1|\tau} \end{pmatrix} = \begin{pmatrix} \hat{\mu}_{i1,\tau} \\ \hat{\mu}_{i2,\tau} \end{pmatrix} + \sum_{p=1}^{P} \hat{\Gamma}^{(\circ)}_{ip} \begin{pmatrix} IU_{i,\tau-p+1} \\ \pi_{i,\tau-p+1} \end{pmatrix} + \sum_{p=1}^{P} \hat{\Psi}_{ip} \begin{pmatrix} y^{\bullet}_{i,\tau-p+1} \\ y^{\bullet}_{i,\tau-p+1} \end{pmatrix}, \tag{7.2}$$

[2] Alternative levels of 10% or 1% obtain qualitatively equivalent results.

where '$\circ$' refers to estimates under distinct hypotheses[3] $\circ \in \{H_{01}, H_{02}, H_1\}$. Within time windows W_k, $k = 2, ..., K$, forecasts are based on estimates $\hat{\mu}_{i1,\tau}, \hat{\mu}_{i2,\tau}, \hat{\Gamma}^{(\circ)}_{ip}$ and $\hat{\Psi}_{ip}$ determined within preceeding subperiods W_{k-1}. Predictive accuracy in observation window W_k is assessed by means of mean absolute forecast errors (MAE). This statistic obtains, e.g., as

$$\mathrm{MAE}^{(\circ)}_k(IU_i) \;=\; (1/E_K) \sum_{\tau+1\in W_k} |\hat{IU}^{(\circ)}_{i,\tau+1|\tau} - IU_{i,\tau+1}|, \tag{7.3}$$

and, analogously, for $\pi_{i,\tau+1}$. Cases where $\mathrm{MAE}^{(\circ)}_k(IU_i)$ and $\mathrm{MAE}^{(\circ)}_k(\pi_i)$ are lower for predictions from (7.2) under H_1 than under H_{01} and H_{02}, respectively, are regarded as evidence for the FB or CM hypothesis, respectively. Rejections of H_0 obtain if predictions under H_{01} and H_{02} are both outperformed by those under H_1. The Diebold-Mariano (1995, DM) statistic is employed to assess significance of OS performance differentials.

7.3 Results

For each instance out of K (subsamples) $\times$ 22 (economies) an IS F-test is obtained. For OS modelling the number of DM-tests is $(K-1) \times 22$. IS and OS statistics are reported as rejection frequencies in Tables 7.1 and 7.2, respectively. As indicated in the tables, we determine alternative output gap measures, $\tilde{y}^{HP}_\tau$ and $\tilde{y}^{CF}_\tau$, by means of the Hodrick-Prescott or the Christiano-Fitzgerald filter, respectively. Cross-sectional averages of correlations between alternative measures are $\mathrm{Corr}\big[\tilde{y}^{HP}_\tau, \tilde{y}^{CF}_\tau\big]$=0.56, $\mathrm{Corr}\big[\tilde{y}^{HP}_\tau, \Delta_{12} y_\tau\big]$=0.63 and $\mathrm{Corr}\big[\tilde{y}^{CF}_\tau, \Delta_{12} y_\tau\big]$=0.48. Owing to moderate correlation, each process may provide distinct context information to assess the causal linkage between inflation and IU. IS rejections of H_{01} indicate stronger evidence in favour of FB

[3] One might also depart from a priori restricting A_{ip} according to H_0 and regard $H_{01}, ..., H_{04}$ and H_1 as distinct alternatives. However, due to the omitted variables bias we consider H_1 as a more suitable reference.

than rejections of H_{02} for CM. Given the indications of bidirectional causality (rejections of H_0), such a finding might be of minor relevance for economic policy. Therefore it is noteworthy that rejections of conditional hypotheses H_{03} and H_{04} also support the FB hypothesis. Particularly, rejections of H_{03} amount to about half of the rejections of H_{01}, underlining the viability of targeting inflation as a means to moderate IU. Similarly, comparing OS rejection rates of H_{01} and H_{02} is supportive of FB in comparison with CM. Thus, inflation is a more informative predictor variable for IU than vice versa. Regarding robustness of inferential results favouring FB, we do not find that structural changes strongly affect the relation between inflation and IU. Results hold irrespective of the choice of window lengths and the consideration of subsample results for the 1990s and 2000s.

7.4 Summary

We find evidence favouring the impact of inflation on IU as suggested by Friedman (1977) and Ball (1992) over the reverse direction of causality (Cukierman and Meltzer 1986; Devereux 1989) for a sizeable number of developed economies. This reinstates the findings from chapter 4, where it is documented that the CM effect is less pronounced than other causal relations. Diagnostic results are qualitatively robust with respect to the choice of sample periods, estimation window size, IU measures and other specification characteristics.

Table 7.1: IS tests of causality

	HP					CF					Δ_{12}				
	H_0	H_{01}	H_{02}	H_{03}	H_{04}	H_0	H_{01}	H_{02}	H_{03}	H_{04}	H_0	H_{01}	H_{02}	H_{03}	H_{04}
K	$\hat{\sigma}_{\tau+1\|\tau}$														
14	0.56	0.45	0.34	0.30	0.19	0.51	0.42	0.33	0.29	0.20	0.53	0.40	0.33	0.28	0.21
9	0.45	0.39	0.26	0.22	0.09	0.53	0.48	0.35	0.20	0.08	0.55	0.46	0.32	0.24	0.10
7	0.56	0.49	0.32	0.22	0.05	0.54	0.50	0.35	0.20	0.05	0.50	0.49	0.33	0.18	0.02
5	0.51	0.47	0.35	0.15	0.03	0.43	0.40	0.25	0.18	0.03	0.42	0.41	0.20	0.22	0.01
1990s	0.52	0.45	0.31	0.30	0.15	0.45	0.38	0.29	0.27	0.17	0.42	0.34	0.27	0.23	0.15
2000s	0.22	0.17	0.14	0.12	0.09	0.22	0.19	0.13	0.13	0.08	0.27	0.19	0.15	0.13	0.10
K	$\hat{a}_{\tau+1}$														
14	0.61	0.59	0.47	0.23	0.10	0.64	0.66	0.46	0.28	0.08	0.62	0.65	0.48	0.25	0.08
9	0.70	0.68	0.57	0.13	0.03	0.63	0.62	0.53	0.10	0.02	0.61	0.58	0.51	0.10	0.03
7	0.55	0.54	0.48	0.06	0.01	0.58	0.58	0.48	0.09	0.00	0.59	0.58	0.51	0.08	0.01
5	0.56	0.56	0.45	0.10	0.00	0.58	0.58	0.53	0.05	0.00	0.56	0.56	0.50	0.06	0.00
1990s	0.55	0.55	0.43	0.20	0.08	0.55	0.56	0.40	0.23	0.08	0.56	0.60	0.41	0.25	0.06
2000s	0.28	0.26	0.20	0.11	0.05	0.30	0.31	0.21	0.13	0.03	0.27	0.28	0.22	0.09	0.03
K	$\bar{\sigma}_{\tau+1\|\tau}$														
14	0.57	0.48	0.31	0.36	0.19	0.56	0.48	0.32	0.33	0.17	0.58	0.45	0.36	0.29	0.20
9	0.64	0.57	0.45	0.20	0.08	0.59	0.55	0.40	0.19	0.05	0.59	0.56	0.42	0.19	0.05
7	0.61	0.59	0.41	0.20	0.02	0.55	0.53	0.33	0.22	0.02	0.55	0.54	0.39	0.16	0.02
5	0.51	0.52	0.33	0.20	0.01	0.51	0.51	0.34	0.18	0.01	0.47	0.47	0.31	0.16	0.00
1990s	0.51	0.41	0.30	0.27	0.16	0.56	0.47	0.32	0.31	0.16	0.54	0.40	0.34	0.27	0.21
2000s	0.25	0.21	0.14	0.17	0.10	0.22	0.19	0.13	0.13	0.08	0.24	0.20	0.16	0.12	0.09

Cell entries represent rejection frequencies of IS tests regarding $H_0, ..., H_{04}$ at the 5% level of significance. The number of tests is $K \times 22$, the product of nonoverlapping time windows and economies. Labels "HP", "CF" and "Δ_{12}" refer to results obtained for distinct output measures. Rows labelled '1990s' and '2000s' report rejection frequencies for subperiods W_k comprising observations from respective decades, with $E_5 = 24$. Results for the 10% or 1% significance level are qualitatively similar and available from the authors on request.

Table 7.2: OS tests of causality

	HP			CF			Δ_{12}		
	H_0	H_{01}	H_{02}	H_0	H_{01}	H_{02}	H_0	H_{01}	H_{02}
K	$\hat{\sigma}_{\tau+1\|\tau}$								
14	0.06	0.28	0.16	0.05	0.22	0.18	0.06	0.25	0.19
9	0.06	0.26	0.22	0.11	0.25	0.28	0.04	0.19	0.21
7	0.06	0.24	0.24	0.08	0.21	0.31	0.02	0.17	0.20
5	0.02	0.18	0.31	0.06	0.23	0.23	0.06	0.24	0.31
1990s	0.05	0.21	0.17	0.04	0.16	0.14	0.06	0.17	0.18
2000s	0.02	0.15	0.05	0.02	0.11	0.09	0.03	0.14	0.08
K	$\hat{a}_{\tau+1}$								
13	0.04	0.24	0.13	0.02	0.20	0.10	0.04	0.24	0.12
8	0.02	0.31	0.06	0.02	0.34	0.05	0.03	0.30	0.08
6	0.01	0.24	0.04	0.03	0.30	0.05	0.01	0.20	0.07
4	0.05	0.20	0.07	0.01	0.20	0.05	0.02	0.19	0.09
1990s	0.02	0.22	0.10	0.01	0.19	0.06	0.03	0.19	0.08
2000s	0.02	0.11	0.06	0.01	0.09	0.06	0.02	0.12	0.06
K	$\bar{\sigma}_{\tau+1\|\tau}$								
13	0.05	0.20	0.21	0.05	0.18	0.22	0.05	0.18	0.21
8	0.04	0.18	0.22	0.03	0.20	0.22	0.04	0.20	0.22
6	0.02	0.14	0.19	0.03	0.12	0.31	0.04	0.11	0.27
4	0.05	0.25	0.17	0.05	0.17	0.27	0.06	0.16	0.24
1990s	0.03	0.17	0.20	0.06	0.19	0.20	0.05	0.17	0.19
2000s	0.03	0.09	0.09	0.01	0.07	0.09	0.01	0.08	0.09

Cell entries represent frequencies where DM tests of respective null hypotheses indicate rejections at the 5% level of significance. The number of tests is $(K-1) \times 22$. For further notes see Table 7.1.

8. THE EURO IMPACT ON INFLATION UNCERTAINTY

8.1 Outline

In chapter 4, it is found that the causal relation between IU and output growth might be more pronounced in economies participating in the EMU than for others. Moreover, the overall level of IU (as measured by GARCH in this case) appears to be different on average for distinct groups of economies. In the following chapter, we focus on the question whether being part of the European Monetary Union (EMU) reduces inflation risks among its member states. The results obtained in chapter 4 indicate that the benefits of low levels of IU might be particularly high in the EMU.

To assess an effect of currency union participation, the level of IU in the EMU is compared to inflation risk in economies which do not take part in the EMU. In contrast to chapter 4, we introduce a model where we compare IU in episodes before and initially after the Euro introduction and during the recent recession. The selection of control groups outside the Euro area serves as a means to approximate a counterfactual situation where no common monetary policy is in effect. The systemic background can be seen as both an independent determinant of IU as a result of monetary policy interventions. Moreover, it might act as a transmission channel for dynamics in output growth, inflation or global influences. Both fortunate and disadvantageous effects of joining a currency union for IU have been described in theory (Alesina and Barro 2002; Davig et al. 2011). In chapter 3, several opposite hypotheses are described.

We argue that effects of monetary unification on IU have to be analysed carefully, since the regime shift coincides with other institutional reforms and marked changes in global inflation dynamics. In particular, the widespread adoption of inflation targeting (IT) strategies (Bernanke et al. 1999) likely affects the IU environment (Kontonikas 2004, Wright 2008, Gavin et al. 2009). Furthermore, the importance of inflation as a determinant of IU (Ball 1992; Friedman 1977) is documented, e.g. in chapter 7 of this thesis. Moreover, Lahiri and Liu (2005) argue that the uncertainty about future dynamics of exchange rates or stock prices, energy price shocks or business cycle fluctuations may also influence IU. Therefore, to narrow down the impact of the Euro introduction, such influences are explicitly taken into account in our empirical approach.

8.2 Model framework

Apart from the impact of monetary policy, we take several potential influences on IU into account which are typically discussed in the theoretical and empirical literature. For instance, the effect of stock market volatility on IU is investigated by Kontonikas et al. (2005). One might argue that returns, being streams of nominal income, should reflect uncertainty about inflation. Gosh et al. (1995) or Gagnon and Ihrig (2001) find that the dynamics of foreign exchange rates affect both the level and the volatility of inflation. Evans and Wachtel (1993) or Barsky and Kilian (2002) describe relations between oil price shocks and inflation, IU and real economic activity. To incorporate measures of aggregate financial and commodity risks, we consider realised standard deviations (Schwert 1989, Andersen, Bollerslev and Diebold 2004) as explanatory variables in our analysis. Such quantities are determined as

$$\mathrm{RS}_\tau(\star) = \sqrt{\sum_{m\in\tau}(\Delta \ln u_m)^2}, \tag{8.1}$$

where an observation at day m is denoted u_m and $\star \in \{FX, oil, dow\}$[1]. Presumably, the US Dollar and the Euro are currently the most important units of account for transactions at the international level. For this reason, exchange rates are considered with respect to the US Dollar for all economies except the US, for which the price of the Euro in US Dollar is used to determine realised uncertainty. In the following Section, our model of IU is introduced. We specify IU as a function of distinguished groups of constitutional, macroeconomic and financial determinants. Implementation particularities of the regression analysis are summarised in Section 4.2.

8.2.1 Modelling influences on IU

The distinct influences on IU are related by means of an analysis of variance (ANOVA) regression for economies $i = 1, \ldots, 18$ in the $\mathcal{M}18$ cross section. Controlling for measurable triggers of IU dynamics, lagged inflation $\pi_{i,\tau-1}$ and economy-specific output gaps $\tilde{y}_{i,\tau-1}$ along with monthly realised standard deviations as collected in $\boldsymbol{z}_{i,\tau-1} = (\pi_{i,\tau-1}, \tilde{y}_{i,\tau-1}, \mathrm{RS}_{\tau-1}(FX), \mathrm{RS}_{i,\tau-1}(oil), \mathrm{RS}_{i,\tau-1}(dow))'$ (see eq. (8.1)) are used for conditioning the IU measures. The ANOVA regression reads as

$$\begin{aligned} IU_{i\tau} &= \mu_\tau + \nu_{i\tau} + \boldsymbol{z}'_{i,\tau-1}\boldsymbol{\varrho} + u_{i\tau}, \quad \tau = \tau_0 - \ell, T_0^* - \ell + 1, ..., T^* - \ell, \\ &\text{with } IU_{i\tau} \in \{\hat{\sigma}_{i,\tau+\ell|\tau}, \hat{a}_{\tau+\ell}, \bar{\sigma}_{i,\tau+\ell|\tau}\}. \end{aligned} \tag{8.2}$$

[1] In chapter 2, a description of these series is provided.

Ciccarelli and Mojon (2010) document that inflation dynamics in industrialised economies might be explained to a large degree by common, or 'global' factors. Such developments might e.g. be the result of the adoption of inflation targeting strategies by many central banks during the last decades. Hence, to isolate the Euro impact on IU, one should control for such common trends. We specify deterministic time features of IU as a low-order time polynomial augmented with a set of trigonometric terms (Gallant 1981). To be precise, μ_τ in (8.2) is formalised as

$$\mu_\tau = \beta_0 + \sum_{c=1}^{C} \beta_c s^c + \sum_{d=1}^{D} \left\{ \phi_d \cos(ds) + \varphi_d \sin(ds) \right\}, s = 2\pi(\tau - T_0^* + \ell)/(T^* - \tau_0). \tag{8.3}$$

Eubank and Speckman (1990) refer to the polynomial trigonometric (PT) model in (8.3) primarily as an efficient means of detrending, but also point out its applicability as a filtering method for nuisance effects within the blocks of an ANOVA design[2]. In (8.2), constitutional determinants of IU are expressed by means of a function of dummy variables,

$$\nu_{i\tau} = \nu_1 \mathrm{DB}_{i\tau}^{(\textsc{emu})} + \nu_2 \mathrm{DB}_{i\tau}^{(\textsc{eu3})} + \nu_3 \mathrm{DA}_{i\tau}^{(\textsc{emu})} + \nu_4 \mathrm{DA}_{i\tau}^{(\textsc{eu3})} + \nu_5 \mathrm{DR}_{i\tau}^{(\textsc{emu})} + \nu_6 \mathrm{DR}_{i\tau}^{(\textsc{eu3})}. \tag{8.4}$$

Dummy variables in (8.4) serve as a means to distinguish European from OECD economies. We compare the level of IU in the $O5$ economies, acting as a reference group, to the economies subjected to monetary unification (EMU) and EU members outside the monetary union (EU3). The association of economies to the latter groups *before* the advent of the Euro (AE) is

[2] As an alternative it turns out that fixed IU time effects offer a rather similar perspective at the global trend in IU. Since the PT regression in (8.3) is by far more parsimonious we do not consider unrestricted time effects any further.

controlled by $\mathrm{DB}_{i\tau}^{(\textsc{emu})}$ and $\mathrm{DB}_{i\tau}^{(\textsc{eu3})}$, respectively, where

$$\mathrm{DB}_{i\tau}^{(\bullet)} = \begin{cases} 1 & \text{if } i \text{ belongs to } \bullet \text{ and } \tau < \mathrm{AE} \\ 0 & \text{otherwise.} \end{cases}$$

Next, we consider dummy variables for the period covering the advent of the common currency in 1999M1 and ending before the recent financial crisis. The AE date is chosen as 1999M1, when the common currency was introduced in the 11 initial EMU economies. Dummy variables for the time *after* the Euro introduction $\mathrm{DA}_{i\tau}^{(\bullet)}$, $\bullet = \mathrm{EMU}, \mathrm{EU3}$, are defined as

$$\mathrm{DA}_{i\tau}^{(\bullet)} = \begin{cases} 1 & \text{if } i \text{ belongs to } \bullet \text{ and } \mathrm{AE} \leq \tau < 2007\mathrm{M}12 \\ 0 & \text{otherwise.} \end{cases}$$

As a robustness check, an alternative break date is specified as AE=1997M1, as some Euro effect might have been anticipated before the official date of monetary unification. For example, Caporale and Kontonikas (2009) provide evidence for changes in the relation between IU and inflation prior to 1999 which might be due to anticipation effects.

In recent years, most industrialised countries witnessed a severe economic downturn. These developments spurred simultaneous monetary and fiscal expansions in many cases. Such large-scale interventions, however, bear the risk of increasing inflation. As a result this period might be regarded as rather distinct from the less turbulent periods preceding the crisis. It is an open question if a currency union provides more or less insurance against inflation risks as compared with single countries (Alesina et al. 2003, Feldstein 2005). This question is of particular interest because many economies are currently experiencing increasing levels of government debt. As Davig et al. (2011) argue, economies participating in a monetary union might be particularly likely to advocate expansionary monetary strategies in order to raise inflation prospects. This would facilitate the reduction of idiosyncratic debt while associated inflation risks are passed on to the entire currency area. For this reason, we compare the capability of the EMU to contain IU during a recession to the respective performance of single economies.

We introduce dummy variables for the NBER recession period (RP) from 2007M12 to 2009M7 in the EMU and EU3 economies as $\mathrm{DR}_{i\tau}^{(\bullet)}$, and $\bullet = \mathrm{EMU}, \mathrm{EU3}$, given by

$$\mathrm{DR}_{i\tau}^{(\bullet)} = \begin{cases} 1 & \text{if } i \text{ belongs to } \bullet \text{ and } \tau \in \mathrm{RP} \\ 0 & \text{otherwise.} \end{cases}$$

8.2.2 Implementation

Firstly, note that $\boldsymbol{z}_{i,\tau-1}$ is lagged by one month with respect to the time instance when IU measures are anticipated to account for potential endogeneity of the forcing variables (Hooker 1996). Moreover, in specifying the PT trend function μ_τ, we set $C = 2$ according to the recommendations of Eubank and Speckman (1990). Furthermore, following Eubank and Speckman (1990), we determine the trigonometric order D by means of a goodness of fit criterion, i.e.

$$\hat{D} = \min_{D} \ \mathrm{CV}(D) = \frac{(T^* - T_0^* + 1)\mathrm{RSS}(D)}{(T^* - T_0^* - 2D - 2)^2}, \tag{8.5}$$

with $\mathrm{RSS}(D)$ denoting the residual sum of squares from (8.2) implied by a particular choice of D from $1 \leq D \leq D_{\max}$, $D_{\max} = 8$. The maximum order implies that the highest admitted frequency is characterised by a period of $\approx$2.25 years which might be seen as a conservative lower threshold to capture business cycle dynamics.

8.3 Results

In this section we relate the IU measures (5.2) to (5.4) to existing approaches which are commonly applied in empirical studies on IU. Next, we summarise and interpret the outcomes of the ANOVA regression in (8.2). If not stated otherwise inferential results are qualified according to the 5% significance level.

8.3.1 Marginal impacts on IU and the global trend

Before interpreting results regarding the impact of institutional determinants, we briefly discuss the influence of several other potential triggers of IU. In Table 8.1, coefficient estimates from (8.2) are reported. Firstly, IU seems to be strongly linked to inflation. Most of the respective coefficients are positive and significant. This holds irrespectively of ℓ and the distinct ways in which IU is measured. Hence we can confirm findings by Grier and Perry (2000) or Hartmann and Herwartz (2012), who document that inflation influences IU. In contrast, estimates regarding the impact of the output gap $\tilde{y}_{i,\tau-1}$ on IU differ in sign and are only in a few cases significant.

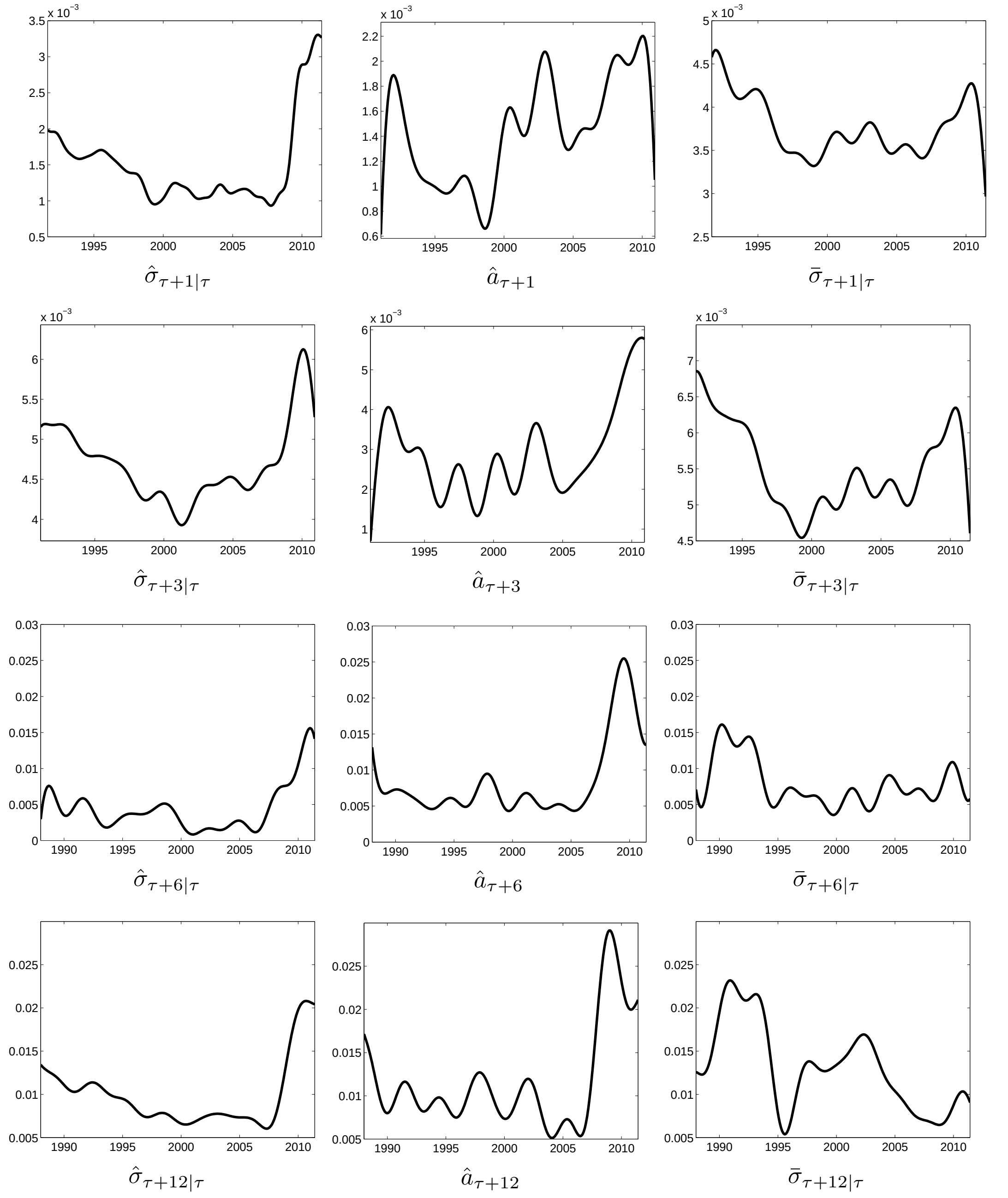
Regarding the influence of volatility variables, it turns out that realised standard deviations of FX rates have a particularly significant effect on IU. Since 10 out of 18 economies from the $\mathcal{M}18$ data set are EMU members, this could be regarded as an indication that risks from bilateral trade with the US are an important source of IU for EMU members. Oil price volatility also seems to be linked to IU to some extent, though the effect is less pronounced than in the case of exchange rate fluctuations. Given the results documented in table 4.1, one might speculate that the effect of oil prices is primarily reflected in the level rather then the uncertainty about inflation. In contrast, the volatility of the Dow Jones index seems to impact in a less significant manner on IU. Moreover, respective coefficient signs are changing

Table 8.1: ANOVA estimates ($\times 10^3$)

	$\ell=1$			$\ell=3$			$\ell=6$			$\ell=12$		
	$\hat{\sigma}_{\tau+\ell\|\tau}$	$a_{\tau+\ell}$	$\bar{\sigma}_{\tau+\ell\|\tau}$	$\hat{\sigma}_{\tau+\ell\|\tau}$	$a_{\tau+\ell}$	$\bar{\sigma}_{\tau+\ell\|\tau}$	$\hat{\sigma}_{\tau+\ell\|\tau}$	$a_{\tau+\ell}$	$\bar{\sigma}_{\tau+\ell\|\tau}$	$\hat{\sigma}_{\tau+\ell\|\tau}$	$a_{\tau+\ell}$	$\bar{\sigma}_{\tau+\ell\|\tau}$
$\mathrm{DB}_{i\tau}^{(\mathrm{EMU})}$	**−0.35**	**−0.30**	−0.35	**−0.73**	**−0.96**	−0.99	**−1.32**	−1.36	−1.23	**−2.60**	**−3.95**	−0.83
	(−2.54)	(−2.00)	(−1.13)	(−2.75)	(−2.19)	(−2.00)	(−2.73)	(−1.34)	(−1.86)	(−3.79)	(−2.81)	(−1.02)
$\mathrm{DB}_{i\tau}^{(\mathrm{EU3})}$	**1.20**	0.26	**5.00**	**2.04**	0.46	7.09	**3.10**	1.88	**8.93**	**4.39**	**4.07**	**10.91**
	(6.55)	(1.24)	(11.92)	(5.73)	(0.76)	(10.48)	(4.76)	(1.38)	(9.93)	(4.74)	(2.12)	(9.91)
$\mathrm{DA}_{i\tau}^{(\mathrm{EMU})}$	**−0.41**	**−0.46**	−0.16	−0.20	−0.82	−0.67	0.97	−0.65	−0.22	−1.13	**−4.96**	−0.81
	(−2.56)	(−2.39)	(−0.44)	(−0.63)	(−1.50)	(−1.10)	(1.61)	(−0.51)	(−0.26)	(−1.23)	(−2.88)	(−0.74)
$\mathrm{DA}_{i\tau}^{(\mathrm{EU3})}$	0.10	0.27	−0.11	0.79	1.60	−0.46	0.95	**5.97**	−0.67	−0.25	**10.34**	−0.58
	(0.41)	(0.90)	(−0.20)	(1.59)	(1.90)	(−0.49)	(1.00)	(3.12)	(−0.51)	(−0.17)	(3.89)	(−0.33)
$\mathrm{DR}_{i\tau}^{(\mathrm{EMU})}$	−0.31	−0.22	−0.72	**−1.25**	−0.80	−0.77	−1.90	0.24	−0.75	−0.73	**−4.96**	−1.50
	(−1.73)	(−1.01)	(−1.76)	(−3.58)	(−1.31)	(−1.15)	(−2.91)	(0.17)	(−0.83)	(−0.76)	(−2.61)	(−1.31)
$\mathrm{DR}_{i\tau}^{(\mathrm{EU3})}$	**−0.75**	**−0.86**	−0.78	**−1.92**	**−3.01**	−1.24	−1.55	**−5.37**	−0.88	0.67	**−9.76**	−1.05
	(−2.69)	(−2.58)	(−1.21)	(−3.45)	(−3.15)	(−1.17)	(−1.48)	(−2.47)	(−0.60)	(0.42)	(−3.25)	(−0.55)
$\pi_{i,\tau-1}$	**12.22**	**12.74**	**14.46**	**23.60**	**40.35**	31.85	**39.81**	40.89	**39.73**	**80.55**	**172.62**	**68.05**
	(4.65)	(4.04)	(2.40)	(4.64)	(4.47)	(3.29)	(4.25)	(1.97)	(3.09)	(5.89)	(6.07)	(4.20)
$\tilde{y}_{i,\tau-1}$	0.69	**−3.68**	−0.72	1.51	2.40	−2.08	**−5.32**	−1.12	−2.20	−0.79	6.94	−1.25
	(1.51)	(−4.77)	(−0.73)	(1.71)	(1.55)	(−1.25)	(−3.45)	(−0.35)	(−1.07)	(−0.39)	(1.90)	(−0.53)
$\mathrm{RS}_{i,\tau-1}(FX)$	**8.31**	−4.04	**12.89**	8.27	−18.90	26.65	15.32	15.76	**30.13**	−2.69	−37.58	**32.51**
	(3.17)	(−1.04)	(2.18)	(1.63)	(−1.89)	(2.79)	(1.62)	(0.71)	(2.34)	(−0.20)	(−1.28)	(2.01)
$\mathrm{RS}_{i,\tau-1}(Oil)$	**−2.05**	**−3.66**	−0.17	−1.07	**−8.72**	−0.35	**5.84**	**14.36**	−1.20	0.26	14.06	1.36
	(−3.12)	(−3.14)	(−0.12)	(−0.88)	(−3.13)	(−0.15)	(2.80)	(2.29)	(−0.40)	(0.09)	(1.87)	(0.38)
$\mathrm{RS}_{\tau-1}(Dow)$	−1.09	**5.66**	−1.33	−2.84	9.22	−1.96	**14.94**	0.83	1.21	**12.16**	**57.64**	−3.93
	(−0.91)	(2.90)	(−0.48)	(−1.23)	(1.84)	(−0.43)	(3.51)	(0.07)	(0.20)	(2.04)	(4.05)	(−0.56)
ANOVA estimates with alternative AE date ($\times 10^3$)												
$\mathrm{DA}_{i\tau}^{(\mathrm{EMU})}$	**−0.39**	**−0.52**	−0.11	−0.29	**−1.05**	−0.61	0.22	−1.78	−0.57	−0.16	−1.44	−0.15
	(−2.64)	(−3.28)	(−0.37)	(−1.03)	(−2.27)	(−1.20)	(0.42)	(−1.64)	(−0.82)	(−0.19)	(−0.92)	(−0.16)
$\mathrm{DA}_{i\tau}^{(\mathrm{EU3})}$	0.17	0.02	0.69	0.79	0.49	0.59	0.88	2.50	0.49	0.22	5.88	1.41
	(0.81)	(0.08)	(1.49)	(1.93)	(0.72)	(0.77)	(1.14)	(1.58)	(0.46)	(0.18)	(2.63)	(1.02)

across forecast horizons ℓ. The assertion that stock return volatilities are not necessarily positively related to inflation risks has been documented by Schotman and Schweitzer (2000) or Conolly et al. (2005). Similarly, Kontonikas et al. (2005) find a positive relation between stock market volatility and IU in the UK, but also point out that the relation turns negative after the Bank of England has adopted an inflation targeting policy scheme. In addition to these variables, we estimate a global trend as a component of IU. Figure 8.1 depicts such trend estimates for distinct IU measures and forecast horizons. All graphs suggest that, starting from some initially intermediate level, IU is largely reduced prior to the year 2000. Subsequently, IU seems to increase only slowly until the year 2007. This reduction of overall IU might reflect the success of the inflation targeting strategy that was first adopted in New Zealand in 1990. Since then, inflation targeting has become one of the most widespread means of conducting monetary policy in industrialised economies. The success of IT in reducing inflation risks has been documented empirically by Kontonikas (2004) and Wright (2008). Gavin et al. (2009) investigate this issue from a theoretical point of view.

Fig. 8.1: The global inflation uncertainty trend



Trend estimates based on (8.2) at anticipation horizons $\ell = \{1, 3, 6, 12\}$. The considered IU measures are those with the highest predictive content as documented in the forecast comparison in chapter 6.

In contrast to earlier years however, with the unfolding of the global recession around 2007, considerable increases in global IU are detected. This effect is particularly pronounced for the $\hat{\sigma}_{\tau+\ell|\tau}$ and the $\hat{a}_\tau$ measure. As it is documented in the descriptive analysis in chapter 5, the $\bar{\sigma}_{\tau+\ell|\tau}$ IU metric indicates a less abrupt increase in global IU. The timing of this uprise is suggestive in the sense that one might suspect the various interventions of governments to stabilise the economy as its main driving forces. Given these findings, estimation results regarding the various economies' experiences with IU during markedly distinct time periods are described and interpreted in the next section.

8.3.2 The constitutional impact on IU

We discuss the Euro effect by means of a comparative assessment of IU over distinct times and across economies with different systemic preconditions. Parameter estimates for potential constitutional determinants IU as expressed in (8.4) are displayed in Table 8.1. The results indicate that the EMU economies exhibit a lower level of IU already prior to the advent of the Euro relative to $O5$ and EU3 members. This means that economies which subsequently participate in the EMU are in a rather fortunate situation even before the adoption of the common monetary policy. Members of the EU3 group feature an initially higher level of IU as compared to both the EMU and the $O5$, which is suggested by the parameter estimates associated with $\mathrm{DB}_{i\tau}^{(\mathrm{EMU})}$ and $\mathrm{DB}_{i\tau}^{(\mathrm{EU3})}$. In the time after the monetary unification, IU is further reduced relative to the $O5$ in the EMU. The EU3 economies are during this time slightly more exposed to IU than other economies. This is expressed by the coefficient estimates regarding the $\mathrm{DA}_{i\tau}^{(\mathrm{EMU})}$ and $\mathrm{DA}_{i\tau}^{(\mathrm{EU3})}$ dummy variables. This means that in the time after its formation, the EMU has been able to achieve and maintain a lower level of IU than single economies. This pattern regarding coefficient signs holds irrespectively of anticipation horizons and IU measures. The findings confirm the evidence obtained by means of the GARCH model in chapter 4. To further check if results are affected by the choice of the time instance of the advent of the Euro, the ANOVA regression is also implemented for an alternative break date AE=1997M1. The resulting alternative coefficient estimates for $\mathrm{DA}_{i\tau}^{(\text{EMU})}$ and $\mathrm{DA}_{i\tau}^{(\text{EU3})}$ are given in the last rows of Table 8.1. The sign, magnitude and significance of these coefficient estimates is in almost all cases numerically very close (and qualitatively identical) to the results documented for the official Euro introduction in AE=1999M1. Hence a significant advantage of EMU members over EU3 and $O5$ economies is indicated also in the case when anticipation effects are taken into account. Distinct reactions of IU over groups of economies during the global recession between 2007 and 2009 are indicated by $\mathrm{DR}_{i\tau}^{(\text{EMU})}$ and $\mathrm{DR}_{i\tau}^{(\text{EU3})}$. Estimates mainly indicate that IU might have been reduced to a further extent relative to the $O5$ group during the recent recession. Given these findings, there seems to be hardly any evidence for assertions that large budget deficits as currently observed in several European economies might raise overall IU in the monetary union. Our results rather indicate to some extent that further decreases in IU have been realised in the EMU during this time, at least as compared to non-European OECD economies.

8.4 Summary

In this chapter, we assess the Euro impact at different states of the inflation uncertainty environment. The relative success of the Euro area is compared to European economies not participating in the European Monetary Union and other non-European OECD economies. Results show that participation in the European Monetary union appears to provide significant insurance against inflation uncertainty. These findings are robust with regard to the changing macroeconomic conditions industrialised economies have encountered during the last two decades. Moreover, our findings also hold for distinct ways of anticipating the latent inflation uncertainty process. Our estimates indicate that risks of rising inflation currently seem to be cumulating on a global scale. Reliable protection against upcoming threats to inflation might therefore be more important than at any time during the last two decades.

9. INFLATION, INFLATION UNCERTAINTY AND THE FREQUENCY OF PRICE UPDATING

9.1 Outline

Friedman (1977) describes how an indirect impact of inflation on real output emerges via IU as a transmission channel. A reformulation of the Phillips curve relation in such an indirect way might explain instability of estimates of the relation between inflation and measures of the business cycle (Orphanides and Solow 1990). In a widely-cited model by Ball (1992), IU arises mainly in situations when inflation exceeds a certain threshold. Excess inflation might give rise to IU in the form of uncertainty about potential disinflation policies. The argument of Friedman (1977) consists of two separate propositions. Firstly, it describes how IU emerges from (excess) inflation rates. This effect is closely associated with the monetary policy framework. This is reflected in Ball's (1992) formalisation of the Friedman (1977) argument. The second part of the Friedman (1977) conjecture suggests that IU impacts negatively on output growth. Therefore, the strength and significance of the PC relation might be dependent on the level of inflation or IU.

The New Keynesian Phillips curve (NKPC) is the currently most widely used recitation of the PC. The NKPC relates inflation to marginal costs as a measure of real activity. Following Galí and Gertler (1999), marginal costs are quantified by means of the so-called labour share, which is a function of unit labour costs. Moreover, prospective inflation, denoted $\breve{\pi}_{t+1}$ in the following, is assumed to have an influence on $\breve{\pi}_t$. This gives rise to the specification

$$\breve{\pi}_\tau = \beta\breve{\pi}_{\tau+1} + \frac{(1-\alpha)(1-\alpha\beta)}{\alpha}\breve{mc}_\tau + \varepsilon_\tau, \tag{9.1}$$

where $\breve{\pi}_\tau$ denotes inflation and $\breve{mc}_\tau$ represents the labour share as a measure of marginal costs. The NKPC is derived under the assumption that the steady state of inflation equals zero. Consequently, the regression specification in (9.1) does not include an intercept term (Galí and Gertler 1999). In (9.1), $\beta < 1$ is a discount factor. Moreover, the parameter $\alpha \in [0, 1]$ determines the degree of price inertia, where $\alpha \in \{0, 1\}$ refers to cases of immediate adjustment and constant prices, respectively. In the model of Calvo (1983), the duration of nonadjustment amounts to a fixed spell of $1/(1-\alpha)$ time periods for the aggregate price level.

In the framework of the NKPC, both the specification in (9.1) and a shorthand representation with $\kappa \equiv ((1-\alpha)(1-\alpha\beta))/\alpha$ have an economic interpretation. Galí and Gertler (1999) refer to κ as a "reduced form" parameter, and distinguish this quantity from the "structural" coefficients of the NKPC in the form (9.1). Widely cited studies where α is termed a structural coefficient are, e.g. Eggertsson and Woodford (2003) or Smets and Wouters (2003). The notion of a "structural" coefficient, however, indicates that coefficients are invariant with respect to shocks or changes in observable quantities (Hurwicz 1962). Invariance of model parameters is crucial to identify, e.g., the reaction of output growth to a shock in money supply. However, the potential state-dependence of parameters which are widely assumed as structural has been acknowledged in theoretical contributions like Ball et al. (1988), Danziger (1983) or Mankiw (1985). Most of these discussions describe the price adjustment process as a function of inflation or IU. Moreover, evidence from observed price changes at the individual firm level suggests that the inflation rate plays a role in the pricing process (Bils and Klenow 2002; Klenow and Kryvtsov 2008). Gertler and Leahy (2006) derive a NKPC where the Calvo scheme is generalised to allow for state-dependent pricing. Recent studies on DSGE models also document that estimates of "structural" parameters like the price adjustment frequency correlate with inflation rates (Canova 2005; Fernandez-Villaverde et al. 2007). A state-dependent price adjustment coefficient might give rise to distinct reactions of the inflation rate to business cycle fluctuations. Moreover, the conjecture of Friedman (1977), that higher inflation ultimately leads to distortions of the price mechanism might be explained by an effect of inflation and IU on the Calvo parameter. Furthermore, the distinction between constant and state-dependent pricing schemes has important implications for economic policy. Following Woodford (2003) and Lombardo and Vestin (2008), Damjanovic and Nolan (2011) show that only under very restrictive assumptions, the central bank's optimal policy is identical for both the Calvo- and state-dependent pricing schemes. They argue that neglected state-dependence might lead monetary authorities to put too little emphasis on the stabilisation of inflation. Finally, the recurring finding of implausible NKPC parameter estimates has led to doubts about the suitability of the labour share as a measure of marginal costs (Kiley 2007; Wolman 1999). The criticism put forth in these studies is also based on theoretical arguments. However, Wolman (1999), Guerreri (2001) or Galí et al. (2005) point out that it might be the overly restrictive assumption of a constant price updating frequency as implied by the Calvo (1983) scheme that gives rise to estimation problems.

We contribute to this literature by empirically testing for state-dependence in the framework of the structural NKPC. This model is derived from optimisation problem of households and firms and rests on the Calvo (1983) pricing scheme. We investigate if the generalisation of the Calvo pricing scheme might obtain NKPC estimates that are more in line with economic theory than those of the typically employed restrictive form. In particular, we examine whether inflation or IU influence the price setting frequency as expressed by the parameter α. This empirical approach is motivated by theoretical discussions as in Ball et al. (1988), Danziger (1983) or Gertler and Leahy (2006). We abstain from the introduction of lagged inflation in the (9.1) like in the so-called "hybrid" NKPC (Galí and Gertler 1999; Galí 2001). This means that both the NKPC and the generalised pricing specification are entirely based on optimisation principles.

For this purpose, we obtain a so-called functional coefficient representation of the NKPC. This semiparametric model class allows to express functional dependence of parameters on observable factor variables (Cai et al. 2000). Thereby we also complement investigations in previous chapters of this thesis, where relations between distinct variables are conditioned on a fixed number of states like higher or lower inflation rates, say. The case of a constant coefficient is included in this model setup as a special case. Thus, it is possible to test for state-dependence in a straightforward way. One particular difficulty encountered by existing inferential procedures on state-dependence are heteroscedastic features in the disturbances of inflation models like the NKPC (Sims 2001). An important advantage of our approach is that it allows to draw inference on the state-dependence of α by taking potential heteroscedasticity into account. For this purpose, we make use of the so-called factor-based bootstrap (Herwartz and Xu 2009). This scheme resamples factor observations in contrast to drawing from the residuals as it is common, e.g. in the typically employed residual bootstrap. The bootstrap scheme will be described in detail after an introduction of the estimation method.

9.2 Model framework

To examine the potential factor dependence of the Calvo parameter α, the influence of $\breve{\pi}_{\tau+1}$ on $\breve{\pi}_\tau$ and $\breve{mc}_\tau$ is accounted for by means of partial regression prior to the estimation of the state dependent NKPC. To isolate the effect of $\breve{\pi}_{\tau+1}$ on $\breve{mc}_\tau$, we let $\breve{\boldsymbol{mc}} = (\breve{mc}_{T_0^*}, ..., \breve{mc}_{T^*})'$, $\breve{\boldsymbol{\pi}} = (\breve{\pi}_{T_0^*}, ..., \breve{\pi}_{T^*})'$ and $\breve{\boldsymbol{\pi}}_+ = (\breve{\pi}_{T_0^*+1}, ..., \breve{\pi}_{T^*+1})'$, assuming that one additional observation is available[1]. Then, $\boldsymbol{mc} = (I_\mathcal{T} - \breve{\boldsymbol{\pi}}_+(\breve{\boldsymbol{\pi}}_+'\breve{\boldsymbol{\pi}}_+)^{-1}\breve{\boldsymbol{\pi}}_+')\breve{\boldsymbol{mc}}$ where $I_\mathcal{T}$ denotes the identity matrix of dimension $\mathcal{T} = T^* - T_0^* + 1$, whereas $\boldsymbol{\pi} = \breve{\boldsymbol{\pi}} - \beta\breve{\boldsymbol{\pi}}_+$ may be obtained by presetting $\beta = 0.99$. Such magnitudes of the discount parameter β are commonly calibrated for quarterly data (Altig et al. 2005; Dufour et al. 2006; Sbordone 2005; Smets and Wouters 2003). Estimation of β also yields values close to 0.99 (Dufour et al. 2006; Galí and Gertler 1999). Accounting for the effect of $\breve{\pi}_{\tau+1}$ in this way results in an equivalent representation of (9.1). The condensed representation is advantageous since we focus on the state dependence of α. In the following, the bivariate state dependent NKPC representation is introduced. Initially, (9.1) is generalised such that α is a function of only one factor. A specification depending on one factor is a convenient way to introduce the concept and notation. Next, allowing for bivariate state dependence obtains the model employed for subsequent empirical analysis. The state dependent NKPC is given by

$$\pi_\tau = \frac{(1-\alpha(w_\tau^{(\bullet)}))(1-\beta\alpha(w_\tau^{(\bullet)}))}{\alpha(w_\tau^{(\bullet)})} mc_\tau + e_\tau. \tag{9.2}$$

This formulation may be employed to detect changes in firms' price setting behaviour which are driven by some factor $w_\tau^{(\bullet)}$, where '$\bullet$' indicates that either (1) lagged inflation $\pi_{\tau-1}$ or (2) $IU_{\tau-1}$ are potential factor variables. In this

[1] Alternatively, accounting for the effect of $\breve{\pi}_{\tau+1}$ on $\breve{mc}_\tau$ may proceed by means of GMM estimation. This procedure, however, obtains qualitatively equivalent results, which are available from the author upon request.

chapter, we focus on representing IU by means of the $\hat{a}_{\tau-1}$ measure defined in (5.4) for reasons of data availability. To account for different scales of the inflation and IU processes, $w_\tau^{(\bullet)}$ is considered in standardised form, i.e. $w_\tau^{(\bullet)} = (\widetilde{w}_\tau^{(\bullet)} - \bar{w}^{(\bullet)})/\sigma(\widetilde{w})$ with $\bar{w}^{(\bullet)}$ and $\sigma(\widetilde{w})$ denoting the mean and the standard error of $\widetilde{w}_\tau^{(\bullet)}$. Furthermore, inflation and IU might interact in the way they influence firms' price setting (Danziger 1983). To allow for a joint influence of both factors, we specify

$$\pi_\tau = \frac{(1-\alpha(w^{(1)} = w_\tau^{(1)}, w^{(2)} = w_\tau^{(2)}))(1-\beta\alpha(w^{(1)} = w_\tau^{(1)}, w^{(2)} = w_\tau^{(2)}))}{\alpha(w^{(1)} = w_\tau^{(1)}, w^{(2)} = w_\tau^{(2)})} mc_\tau + e_\tau,$$

$$\equiv \frac{(1-\alpha(\omega))(1-\beta\alpha(\omega))}{\alpha(\omega)} mc_\tau + e_\tau. \tag{9.3}$$

where $\omega = (w^{(1)}, w^{(2)})$.

9.2.1 Estimation

Estimation of the factor dependent price adjustment frequency proceeds in analogy to the semiparametric Nadaraya Watson estimation method (Nadaraya 1964, Watson 1964). Furthermore, the potential endogeneity of mc_τ in models like (9.1) has been discussed in a sizeable literature (cf. Galí and Gertler 1999; Sbordone 2005 and the references therein.). Under such circumstances, estimation of the NKPC commonly proceeds by means of the generalised method of moments (GMM). In the framework of the functional coefficient model (9.3), $\alpha(\omega)$ is estimated according to

$$\hat{\alpha}(\omega) = \arg\min_\alpha q(\alpha, K_h(\omega)), \tag{9.4}$$

under the assumption that the GMM objective function

$$q(\alpha, K_h, \omega) = \bar{m}(\cdot)'\Phi\bar{m}(\cdot), \tag{9.5}$$

has a unique minimum. In (9.5), $K_h(u) = K(u/h)/h$, with $K(\cdot)$ being a kernel function depending on the so-called bandwidth parameter $h > 0$. Moreover, Φ represents a positive definite weighting matrix and $\bar{m}(\cdot)$ is shorthand for the (empirical) moment condition

$$\bar{m}(\alpha, K_h, \omega) = (1/\mathcal{T}) \sum_{\tau=T_0^*}^{T^*} z_{\tau-1} e_\tau K_h(w_\tau^{(1)} - w^{(1)}) K_h(w_\tau^{(2)} - w^{(2)}). \tag{9.6}$$

In (9.6), the vector $z_{\tau-1}$ contains instrument variables.

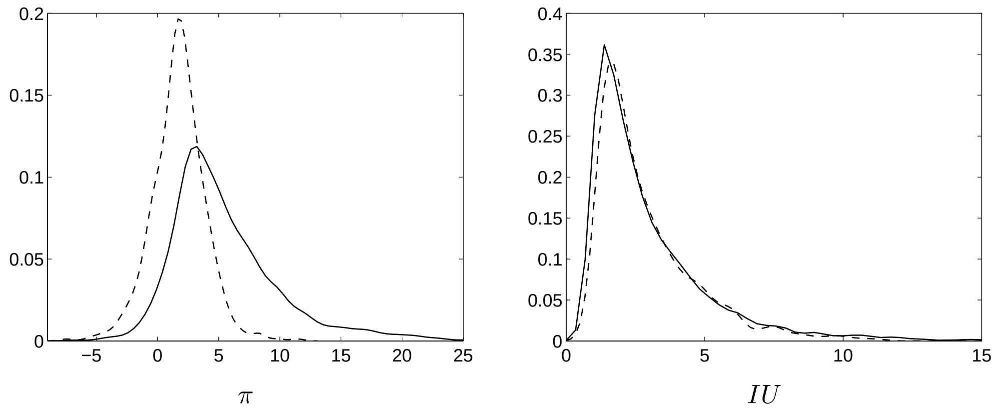
9.2.2 Semiparametric regression and its implementation

Theoretical descriptions of how price adjustment responds to π or IU suggest that nominal rigidity is decreasing for higher inflation rates and in cases of emerging IU (Ball et al. 1988). If the response of α to π or IU is not highly erratic, observations $w_\tau^{(\bullet)}$ near point $w^{(\bullet)}$ should be informative for the value of the functional $\alpha(\pi, IU)$ near $w^{(\bullet)}$ (Eubank 1988; Härdle 1990). In (9.3), the relation between π_t and mc_t is evaluated locally around ω. The kernel weighting function $K_h(\cdot)$ accentuates information in close proximity to ω and discounts the information from more distant observations in the estimation of $\alpha(\omega)$. The bandwidth h determines the scaling of the kernel weighting. While smaller bandwidths tend to increase the variability of estimates, larger values may hide local characteristics of the relation between α and ω. For increasing h, $\hat{\alpha}(\omega)$ approaches the limit of the usual time-invariant GMM estimate. For this reason, it is straightforward to contrast an invariant α from a state-dependent relation by means of the semiparametric regression scheme. We choose the bandwidth according to Scott's rule of thumb (Scott 1992) which obtains as $h = 1.06\mathcal{T}^{-1/5}$ since the factor variables are considered in standardised form. We employ the logistic Kernel, i.e. $K(u) = \Lambda(u)/(1-\Lambda(u))$, where $\Lambda(u) = 1/(1+\exp(-u))$. For the graphical display of the functional dependence $\alpha(w^{(1)} = v^{(1)}, w^{(2)} = v^{(2)})$ is evaluated at particular states $(v^{(1)}, v^{(2)})$ from the 2-dimensional, equidistant grid

$$\begin{aligned} v^{(\bullet)} &= c_{\text{lo}}^{(\bullet)}, c_{\text{lo}}^{(\bullet)} + k^{(\bullet)}\mathcal{L}^{(\bullet)}, ..., c_{\text{up}}^{(\bullet)},\ \bullet \in \{1,2\}, \\ &\quad \text{with } k^{(1)} = 1,2,3,... \text{ and } k^{(2)} = 1,2,3,... \end{aligned} \tag{9.7}$$

In (9.7), $c_{\text{lo}}^{(\bullet)}, c_{\text{up}}^{(\bullet)}$ denote lower and the upper quantiles of the factor observations $w_\tau^{(\bullet)}$, $\tau = T_0^*, ..., T^*$ and $\mathcal{L}^{(\bullet)}$ determines the step length. Particular choices of quantiles from $w_\tau^{(\bullet)}$ are determined to facilitate the graphical exposition and numerical accuracy of results. Functional coefficient estimates feature highest local efficiency at the mode of an empirical factor distribution. In our case, the sample period covers observations from higher inflation regimes from the more distant past. Corresponding levels of π have only in few instances been observed during recent times. A choice of $\{c_{\text{lo}}, c_{\text{up}}\} = \{0.2, 0.8\}$ determines a range of inflation and IU which is currently observed in most advanced economies. In figure 10.1, estimates of the empirical density function for inflation rates which include all $\mathcal{T} \times 14$ observations in the $\mathcal{Q}14$ cross section are shown in the left plot (solid line) along with density estimates for the most recent 10 years of data (dashed line). Apparently, recent years are characterised by a smaller number of outlying observations. The plot on the right shows respective kernel estimates for the IU series. The dispersion of IU during the recent decade is largely similar to the one for the entire sample period. For this reason, we determine $\{c_{\text{lo}}, c_{\text{up}}\} = \{0.01, 0.8\}$ as a suitable range of IU for which local dependence of α is examined.

Fig. 9.1: Inflation rates and IU: Smoothed empirical densities of factor observations



Solid lines correspond to estimates based on all observations in the sample period from 1960Q4 to 2011Q1 in the $\mathcal{Q}14$ cross section. Dashed lines represent estimates for the period between 2001Q2 and 2011Q1.

9.2.3 Inference

In typical applications of the GMM principle, a suitable choice of $z_{\tau-1}$ guarantees that $q(\cdot)$ has a unique minimum. Given that certain additional "regularity conditions" are satisfied, this implies the consistency and asymptotic normality of the estimator (Hayashi 2000). The consistency of the estimator in (9.4) hence relies on the validity of the moment condition in (9.6). The primary aim of our empirical approach, however, is to detect state-dependent variation in α. We note that though $q(\cdot)$ depends on α in a nonlinear way, identification of the sign of changes in α seems to be warranted. Since $\kappa = ((1-\alpha)(1-\alpha\beta))/\alpha$, $\partial(\kappa)/\partial(\alpha) > 0$ if $\alpha > 0.61$ for $\beta \approx 0.99$. In all cases reported below, the range of estimates for α is well above this level. To test if the state invariant relation can be rejected conditional on specific states, Cai et al. (2000), propose a residual bootstrap method. Residual based resampling, however, might be affected by potentially heteroscedastic error terms (Herwartz and Xu 2009). This is particularly relevant since we consider inflation and IU as factors in this study. Conditional heteroscedasticity of such processes is empirically well documented for distinct economies (Engle 1982, 1983; Hartmann and Herwartz 2012). For this reason, we employ the so-called factor-based bootstrap (FaB) as suggested by Herwartz and Xu (2009). This method is based on the resampling of factor observations and proceeds as follows.

1. Functional coefficients evaluated at particular realisations of the data and for a given choice of h may be described as

$$\hat{\alpha}(\omega) = \alpha\left(\pi_\tau, mc_\tau, \omega_\tau = (w_\tau^{(1)}, w_\tau^{(2)}), h, \tau = T_0^*, ..., T^*\right). \tag{9.8}$$

2. To distinguish state dependence from structural constancy in the pricing scheme, local estimates $\hat{\alpha}(\omega)$ are compared to their bootstrap counterparts

$$\hat{\alpha}^*(\omega) = \alpha\left(\pi_\tau, mc_\tau, \omega_\tau^* = (w_\tau^{(1*)}, w_\tau^{(2*)}), h, \tau = T_0^*, ..., T^*\right) \tag{9.9}$$

with binary tuples $(w_\tau^{(1*)}, w_\tau^{(2*)})$ being drawn with replacement from the factor observations $(w_\tau^{(1)}, w_\tau^{(2)})$.

3. A large number as, e.g., $\mathfrak{R} = 1000$ resampling estimates $\hat{\alpha}^*(\omega)$ obtains the bootstrap distribution of $\hat{\alpha}^*(\omega)$. The corresponding confidence interval is employed to assess the local state dependence of $\alpha(\omega)$. In this study, we reject state invariance at the 10% level if $\hat{\alpha}(\omega)$ is either below the 5% or above the 95% -quantile of the bootstrap distribution at any level of the factor variables.

9.3 Results

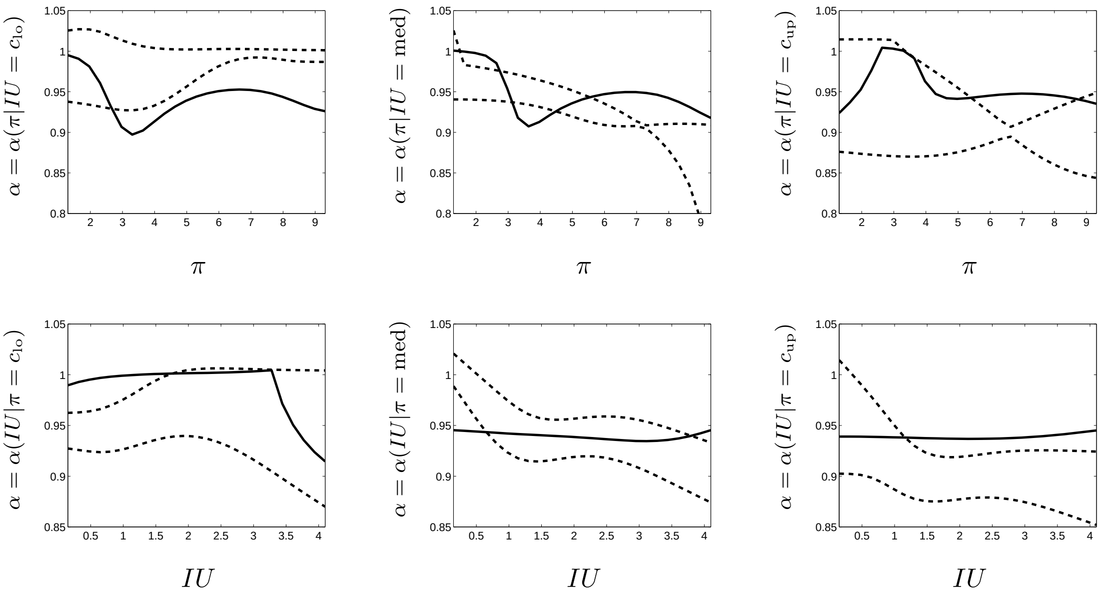
In the preceding chapters, several causal relations are found to depend on specific states of, e.g., the inflation rate, or whether turbulent or tranquil periods are considered. Similarly, there are theoretical arguments for an effect of observable factors on the NKPC pricing scheme (Danziger 1983; Gertler and Leahy 2006). In the following, we report estimates and test outcomes for the dependence of the relation between inflation and marginal costs on inflation or IU as driving factors. After discussing results on the state-dependence of α, we comment on the magnitudes and economic plausibility of implied estimates of the NKPC relation. Estimates are based on the economies in the $\mathcal{Q}14$ cross section. Results from "pooled" estimation, where observations for all economies are jointly considered are also reported. In previous chapters of this thesis, we documented that the considered economies feature distinctive characteristics, particularly with respect to different levels of inflation or IU. Therefore, the conventional pooled estimation framework might be regarded as rather restrictive. However, the functional coefficient representation captures individual economies' idiosyncratic characteristics through the influence of factor variables. This introduces considerable flexibility also in the pooled estimation setting. For this reason, we also abstain from controlling for economy-specific effects in (9.3)[2]. In the figures 9.2, 9.3 and 9.4, estimates obtained according to (9.4) are depicted for the pooled estimate, France, New Zealand and the US. Estimates for the other 10 individual economies are shown in the Appendix. Solid lines represent the estimates $\hat{\alpha}$, dashed lines stand for 90% bootstrap confidence intervals. The latter are obtained according to the FaB as described in section **??**. Local state-dependence at particular factor levels is indicated if estimates are outside the interval. For brevity, we present only a subset of estimates from the entire range of the factor space. Dependence of α on one of the factors is plotted conditional on a certain level of the respective other factor. For example, $\alpha = \alpha(\pi | IU = c_{\text{up}})$ means that poten-

[2] The incorporation of fixed effects for individual economies, however, leaves the estimation outcomes qualitatively unaffected. These results are available from the author upon request.

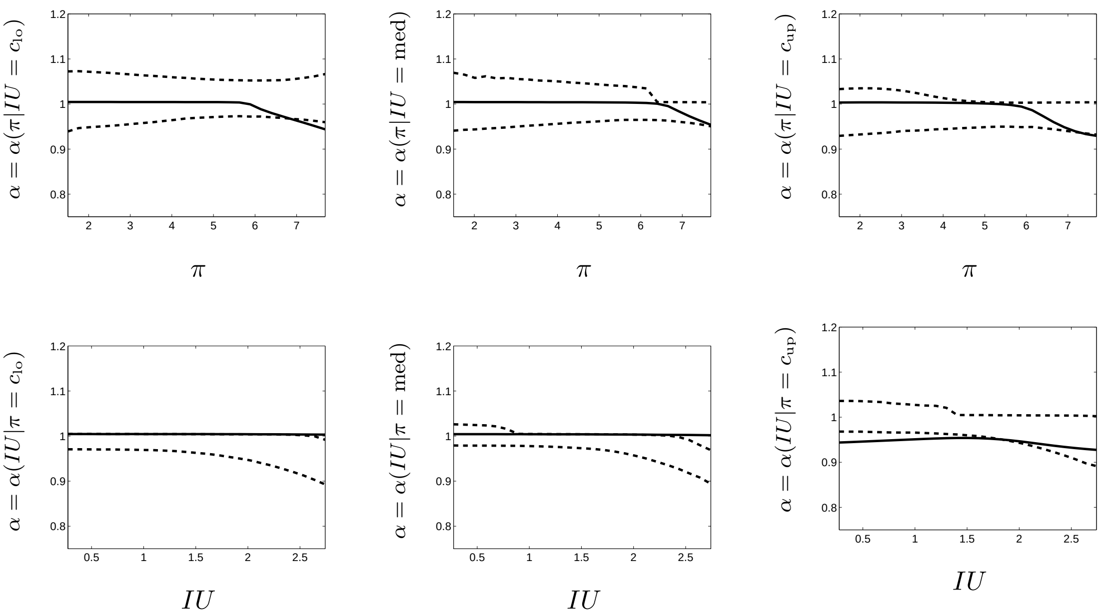
tially inflation-induced variation in α is depicted for an IU level equal to the upper quantile of the IU series. The estimates $\hat{\alpha}$ in figures 9.2 and 9.3 reinstate the theoretical prediction that $\partial\alpha(\omega)/\partial\pi < 0$, i.e. the frequency of price adjustment increases for higher inflation rates. In contrast, we do not find evidence for a uniform sign of the IU impact. This is in line with the discussion in Bénabou (1992) where both signs are described as plausible. However, in almost all cases, an impact of either π or IU on α is detected. Only in the case of Italy the H_0 of a constant Calvo pricing scheme cannot be rejected. In figure 9.4, surface plots for the US and a pooled estimate are depicted to provide an impression on the joint impact of π and IU on α. Surfaces for the remaining individual economies are qualitatively similar and not reported to economise on space. Both plots show that while α takes an initially high level for low inflation rates, the estimates drop at intermediate levels of π around 3%. In case of the pooled estimate, the updating frequency is less responsive for higher π. In both cases, a low frequency of price adjustment prevails for π up to around 5%. Above this value, more rapid updating occurs, where numbers reduce to a magnitude below $\alpha = 0.9$ for intermediate levels of π and IU. At first, the price inertia for values of π which are currently observed in most advanced economies might appear relatively high. This is in contrast to empirical studies where individual firms' price setting data is examined. Altig et al. (2005) note that in studies at the microeconomic level, lower levels of α are reported. The magnitude of α, however, is close to estimates reported in other studies which investigate aggregate pricing (Levin et al. 2006; Smets and Wouters 2003). The influence of IU on α is in both cases confined to moderate inflation rates. However, this range of inflation is also currently most frequently observed. Whereas higher IU leads to decreasing α in the US for low π, the effect is ambiguous in case of the pooled estimate. This suggests as that IU influences α in a rather idiosyncratic way.

Fig. 9.2: Functional coefficient estimates for the pooled sample and France

POOLED SAMPLE

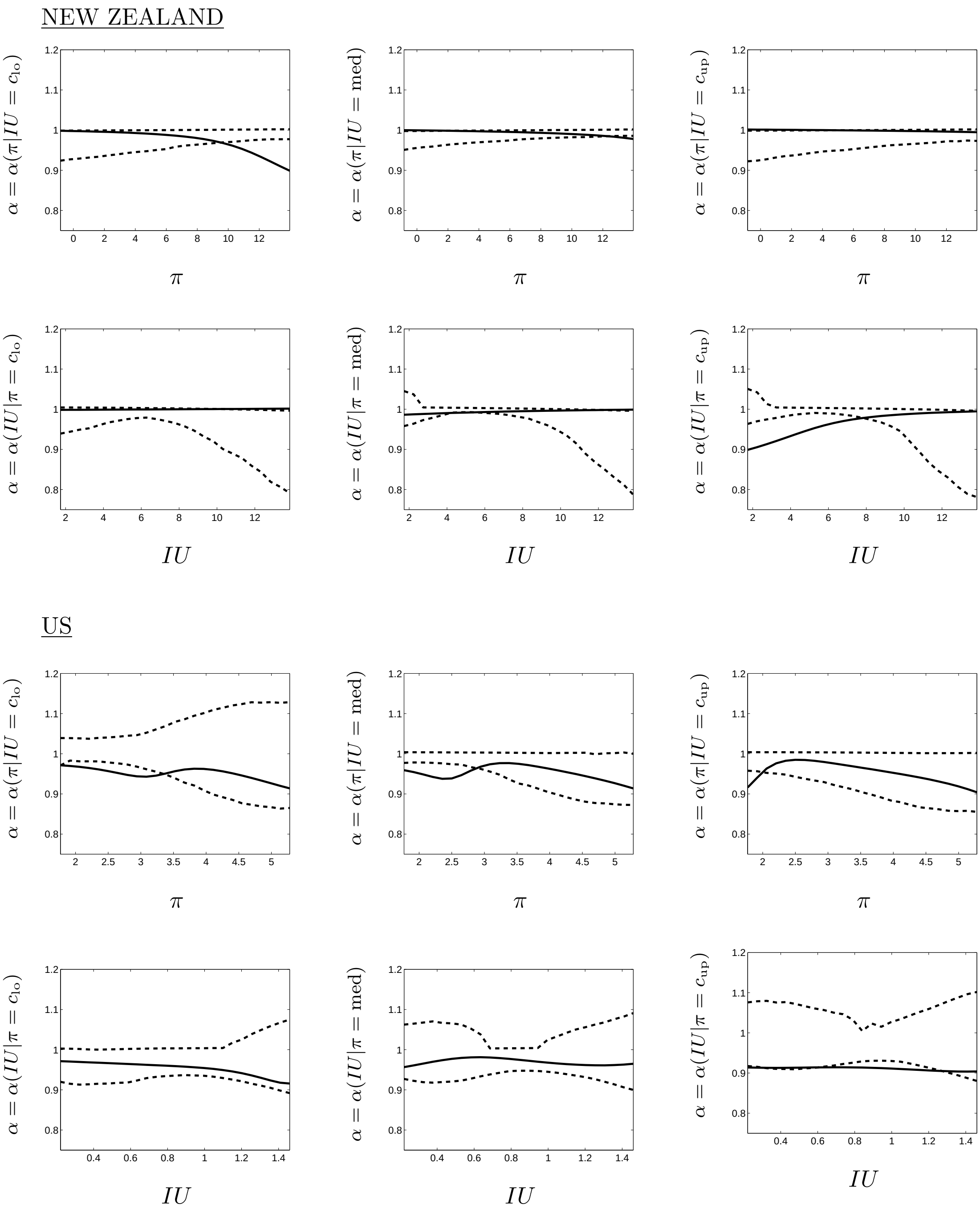


FRANCE



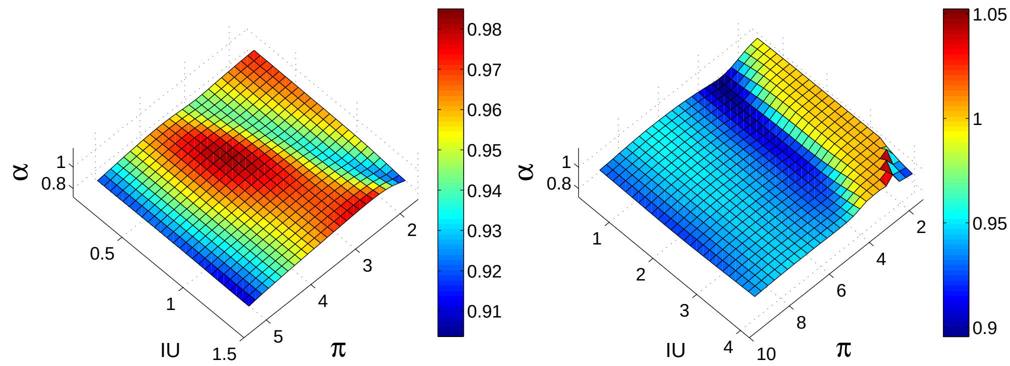
The plots depict the dependence of α on either π or IU, conditional on 3 distinct levels $(c_{\text{lo}}, \text{median}, c_{\text{up}})$ of the respective other factor. For π, $c_{\text{lo}}, \text{median}, c_{\text{up}}$ refer to the lower 20% quantile, the median and the upper 80% quantile. In the case of IU, the lower 0.01% quantile, the median and the upper 80% quantile are considered.

Fig. 9.3: Functional coefficient estimates for New Zealand and the US



For a description see figure 9.2.

Fig. 9.4: Surface plots for the US and the pooled sample



Estimates for US data are depcted in the left plot, pooled estimates on the right hand side.

In table 9.1, diagnostic test statistics are summarised. These statistics are obtained for estimates of (9.1) assuming no state-dependence of α. ARCH-LM tests (Engle 1982) confirm the presence of conditional heteroscedasticity in the residuals for each considered economy. The presence of heteroscedastic features is also documented in section 2 for the $\mathcal{M}34$ data set. The test results reported in this chapter document that ARCH is also detected for the quarterly series in the $\mathcal{Q}14$ cross section. Our findings are in line with those of Fernandez-Villaverde et al. (2007), who point out that ARCH-effects might lead to spurious conclusions regarding state-dependence or dynamics in α. This suggests that the FaB approach might be a more suitable means to draw inference on functional dependence of coefficients. Moreover, the J-statistics in table 9.1 indicate no evidence against the null hypothesis of joint exogeneity of the instrument variable (IV) set. We choose $z_{\tau-1} = (\tilde{y}_{\tau-1}, \tilde{y}_{\tau-2})'$ as instrument variables, where $\tilde{y}_{\tau-1} = y_{\tau-1} - \bar{y}_{\tau-1}$ denotes the output gap. In Galí and Gertler (1999), who focus on US data, additional IV are employed. However, the informative content of many of the employed IV might be limited (Dufour et al. 2006). Choosing $z_{\tau-1} = (\tilde{y}_{\tau-1}, \tilde{y}_{\tau-2})'$ as a subset of their instrument variables results in overall lowest J-statistics for the entire set of considered economes. With 2 instrument variables, the J-test for overidentification adheres to a $\chi^2(1)$ distribution under the H_0 of instrument variable exogeneity.

Table 9.1: Regression diagnostics

	ARCH(1)	ARCH(4)	$J \times 10^3$		ARCH(1)	ARCH(4)	$J \times 10^3$
AU	41.70	52.07	0.09	JP	18.89	26.01	0.01
BE	9.24	24.41	0.01	NL	32.37	111.74	0.32
CA	28.61	33.40	0.03	NZ	41.31	53.47	7.21
ES	34.94	42.81	0.01	PT	38.44	52.26	0.04
FN	74.89	102.17	0.97	SW	76.26	81.09	0.01
FR	42.67	51.31	0.51	UK	77.99	79.46	0.00
IT	26.25	42.10	0.12	US	43.99	51.42	0.01

Table entries report ARCH-LM test statistics (Engle 1982) for the residuals from estimation of (9.1) with $q = 1, 4$ denoting the lag order of squared disturbances. Furthermore, J-test statistics for overidentifying restrictions in the GMM estimation procedure are reported. All reported estimation results are obtained under the assumption of a constant α.

A further way to assess the plausibility of the obtained estimates is to examine the magnitude and significance of the reduced-form parameter $\kappa \equiv ((1-\alpha)(1-\alpha\beta))/\alpha$. A puzzling finding of most studies which follow Galí and Gertler (1999) in using mc_t as an explanatory variable in the structural NKPC is that estimates of κ are insignificant or have a theoretically implausible negative sign (Rudd and Whelan 2007; Sbordone 2005). Table 9.2 shows estimates for the reduced-form NKPC as they are typically reported in related studies. For the economies we consider, the sign of the PC relation is positive, as predicted by economic theory. The magnitudes of estimates are for all economies similar to the findings reported by Galí and Gertler (1999), Galí et al. (2001) or Sbordone (2005), among many others. Moreover, in line with existing empirical evidence, none of the coefficients is statistically significant[3].

It has been noted above that state-dependence of NKPC parameters has

[3] As disturbances are found to be heteroscedastic, t-statistics are based on a robust covariance estimator (Newey and West 1987).

Table 9.2: Estimates for equation (9.1) (constant α case)

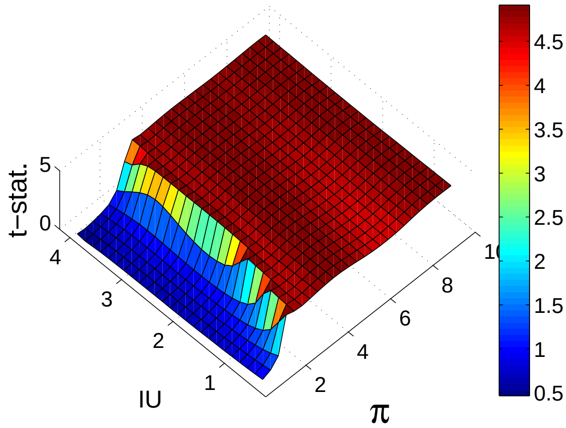
	κ	t-stat.		κ	t-stat.
AU	0.01	0.01	JP	0.01	0.01
BE	0.02	0.02	NL	0.01	0.01
CA	0.01	0.01	NZ	0.02	0.11
ES	0.02	0.03	PT	0.02	0.25
FN	0.01	0.02	SW	0.03	0.02
FR	0.02	0.03	UK	0.05	0.06
IT	0.01	0.11	US	0.01	0.01

Reduced form Phillips curve estimates κ and corresponding t-statistics based on Newey and West (1987) standard errors.

been put forth as an explanation for implausible estimates reported in extant empirical studies (Galí et al. 2005; Wolman 1999). This hypothesis can be addressed by means of the functional coefficient framework. In analogy to the investigation described above, we estimate the reduced-form NKPC, allowing for state-dependence such that $\kappa = \kappa(\omega)$. Since functional dependence of α is detected in the majority of economies[4], the same might also hold for κ. Local estimates of κ and corresponding t-statistics for distinct levels of π and IU indicate if the generalisation reinstates the theory with empirical NKPC estimates. We find that allowing for state-dependence of κ obtains estimates at similar magnitudes as reported in table 9.2. The t-statistics are in most cases higher than their counterparts in table 9.2 but are, however, throughout insignificant also in this case. However, insufficient degrees of freedom might deteriorate the power of t-tests to a larger extent than in the parametric case.

[4] Functional coefficient estimates which allow for state dependence of both α and the discount parameter β suggest that β is not affected by either π or IU. These results are not reported in detail and might be obtained from the author upon request.

Fig. 9.5: State-dependent t-statistics for the reduced-form Phillips curve parameter κ



We therefore compare pooled estimates under the assumption of a constant and state-dependent κ. As depicted in figure 9.5, the t-statistics for functional coefficient estimates of κ are highly significant for inflation levels above $\approx 1.5\%$ for low levels of IU. For higher IU, the inflation level above which the t-statistics indicate significance amounts to $\approx 2.5\%$. The respective state-invariant pooled t-statistic, in contrast, is equal to 1.04. Though significance tests for individual economies are not rejected, these findings suggest that state-dependence is a meaningful generalisation of the Calvo scheme.

9.4 Summary

In this chapter, the method of functional coefficient regression is applied to investigate on the state-dependence of the frequency of price updating. We find that both the inflation rate and IU significantly affect aggregate price adjustment. This confirms theoretical assertions of Friedman (1977), Danziger (1983) or Ball et al. (1988) on the dependence of the (NK)PC relation on the actual level of inflation and IU. Inference is based on a bootstrap methodology which is unaffected by heteroscedasticity in the regression disturbances. Nonspherical disturbances have been described as a principal impediment to valid inference in previous empirical examinations of state-dependent pricing rules. We find that the updating frequency increases at higher inflation rates. Moreover, functional coefficient estimates of the PC relation are found to be more in line with theoretical predictions than estimates obtained under the assumption of constant coefficients.

10. CONCLUSION

This thesis is concerned with the determinants and potential consequences of inflation and inflation uncertainty. Both the sources and effects of inflation uncertainty are controversially discussed. Similarly, theory and empirical evidence on the circumstances in which the effects of both inflation and inflation uncertainty are most relevant are ambiguous. Moreover, since inflation risks are not directly observable, a plentitude of alternative ways to measure this latent quantity have been proposed. We therefore discuss distinct ways of inflation uncertainty measurement. By means of alternative inflation uncertainty measures, we then examine policy-relevant causal linkages.

A widely used tool for uncertainty measurement and causal analysis are (G)ARCH specifications. We adopt such an approach in chapter 4 for the analysis of the linkages between inflation, output growth and their respective uncertainties. By means of a bivariate GARCH model, we approximate uncertainty and draw inference on the respective causal relations. However, GARCH approaches require relatively long sample periods to allow for clear-cut inference. This might give rise to specification problems since macroeconomic processes are likely to undergo structural change. In the first part of this thesis, we address this issue by conducting inference based on the cross sectional variation of a large number of economies. Moreover, we note that during the era of inflation targeting, largely homogeneous dynamics in inflation rates and output growth have been observed on a global scale. Therefore, we limit the sample period to the two most recent decades. This empirical layout reduces the potential impact of unmodelled regime switches in the inflation and output (uncertainty) process on the resulting estimates. Most importantly, we find that inflation and inflation uncertainty have a negative influence on output growth. Second, economy-specific output growth is strongly related to the global business cycle. Third, a significant component of inflation is driven by oil price dynamics. Presuming that central banks can influence the inflation rate, these findings underscore the importance of monetary policy for the real economy. Since inflation uncertainty impacts on output growth in addition to inflation, stabilisation policies might be an important precondition for economic growth. In this respect, the significant influence of oil prices on inflation might be interpreted as a caveat regarding a focus on core inflation as the objective of monetary policy.

In chapter 5, we introduce a set of forecasting-based inflation uncertainty measures. A principal distinction may be drawn between time-series measures and those which approximate inflation uncertainty by means of the disparity among a set of forecasting models. All methods are introduced with an emphasis on quantifying inflation uncertainty from a time-local perspective. Thus, these inflation uncertainty metrics are generally less dependent on the availability of a homogeneous sample period than pertinent GARCH specifications.

The causal relations tested in chapter 4 are reevaluated by means of the forecasting-based uncertainty metrics in the subsequent chapters. In chapter 6, the impact of inflation uncertainty on long term interest rates is documented. It is investigated which of the alternative inflation uncertainty measures is the most informative predictor variable for interest rates in an accordingly augmented Fisher relation. All proposed measures feature higher predictive content than GARCH quantifications and survey measures of inflation uncertainty. Furthermore, one candidate from the set of model-based disparity measures of inflation uncertainty is identified as the strongest predictor variable. These results are found robust across a sizeable number of economies, turbulent and calm periods and with respect to distinct economy-specific inflation experiences in the past. Since the influence of inflation uncertainty is positive for the most informative uncertainty measures, we conclude that this influence should be referred to as an inflation risk premium.

In chapter 7, we investigate the causal relation between inflation and inflation uncertainty. Both in-sample and out-of-sample evidence suggests that the impact of inflation on its associated uncertainty is stronger than vice versa. These results suggest that strategies of raising inflation targets to magnitudes above 2% as it is currently proposed (Blanchard et al. 2010) might also increase inflation risk.

In chapter 8 we highlight the importance of the institutional conditions of monetary policy for inflation uncertainty. In chapter 4, it is documented that being a member of the European Monetary Union might pay off in terms of reduced inflation uncertainty. This finding is reexamined in the framework of a cross sectional empirical model for inflation uncertainty. Particular emphasis is put on the approximation of a counterfactual situation where no common currency is in effect. Results show that members of the European Monetary Union are characterised by significantly lower inflation uncertainty than other economies. Most remarkably, the global trend in inflation uncertainty slopes upward since the emergence of the economic crisis in 2008. In chapter 4, it is documented that output growth is most strongly affected by inflation uncertainty in the Euro economies. This finding underscores the importance of the insurance provided by the monetary union against inflation risk.

Finally, the evidence on the relation between inflation and output obtained by means of the VARX-MGARCH-M model in chapter 4 is reexamined in the framework of a structural representation of the Phillips curve (Galí and Gertler

1999). This specification is commonly derived from a rather restrictive price setting scheme, which has been introduced by Calvo (1983). We document systematic variation of the price setting coefficient in the structural Phillips curve. In particular, the frequency of price adjustment is found to be affected by inflation and inflation uncertainty. Since more rapid adjustment is generally assumed to imply higher search costs for consumers, this finding underscores that higher inflation and inflation uncertainty lead to distortions in the price mechanism (Friedman 1977). In this sense, chapter 9 provides an explanation for the negative effect of both inflation and its uncertainty on output growth as it is documented in the chapters before.

11. APPENDIX

11.1 Inflation forecasting models for IU anticipation

Extending the baseline AR in (5.1) with an output gap term, $\tilde{y}_t = y_t - \bar{y}_t$, yields the backward looking Phillips curve following e.g. Stock and Watson (2007), i.e.

$$\pi_{t+\ell} = \varphi_{10} + \varphi_{11}t + \varphi_{12}\pi_t + \varphi_{13}\tilde{y}_t + \epsilon_{t+\ell}, \quad t = \tau - B + 1, ..., \tau. \tag{11.1}$$

In (11.1), $\tilde{y}_t$ is estimated recursively based on observations $t = \tau - B + 1, ..., \tau$ by means of the Hodrick-Prescott filter with smoothing parameter 129600 (Ravn and Uhlig 2002). Moreover, the growth rate of core money, denoted $\bar{\mathfrak{m}}_t$, is often interpreted as a proxy for inflation expectations. Stock and Watson (2008) obtain a specification which reads as

$$\pi_{t+\ell} = \varphi_{20} + \varphi_{21}t + \varphi_{22}\pi_t + \varphi_{23}\tilde{y}_t + \varphi_{24}\bar{\mathfrak{m}}_t + \epsilon_{t+\ell}. \tag{11.2}$$

Neumann and Greiber (2004) propose to augment (11.2) with an indicator of energy prices obtaining

$$\pi_{t+\ell} = \varphi_{30} + \varphi_{31}t + \varphi_{32}\pi_t + \varphi_{33}\tilde{y}_t + \varphi_{34}\bar{m}_t + \varphi_{35}\Delta^2 oil_t + \epsilon_{t+\ell}. \tag{11.3}$$

In (11.3), $\Delta^2 oil_t$ denotes second differences of the log oil price in terms of domestic currency. Note that (11.3) implicitly comprises log foreign exchange rate changes as predictors of inflation. An alternative model in the spirit of

Cogley (2002) incorporates the deviation of inflation from its long run trend, denoted $\tilde{\pi}_t = \pi_t - \bar{\pi}_t$. This model is given by

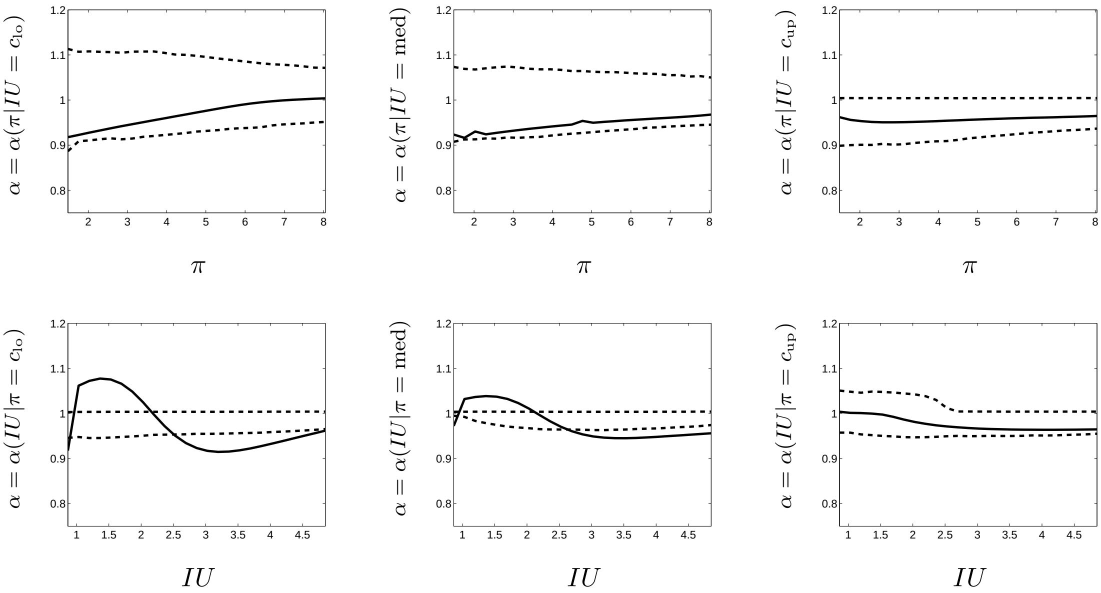
$$\pi_{t+\ell} = \varphi_{40} + \varphi_{41}\tilde{\pi}_t + \epsilon_{t+\ell}. \tag{11.4}$$

This specification expresses the view that that in states deviating markedly from the long run inflation trend, additional adjustment dynamics might impact on $\pi_{t+\ell}$.

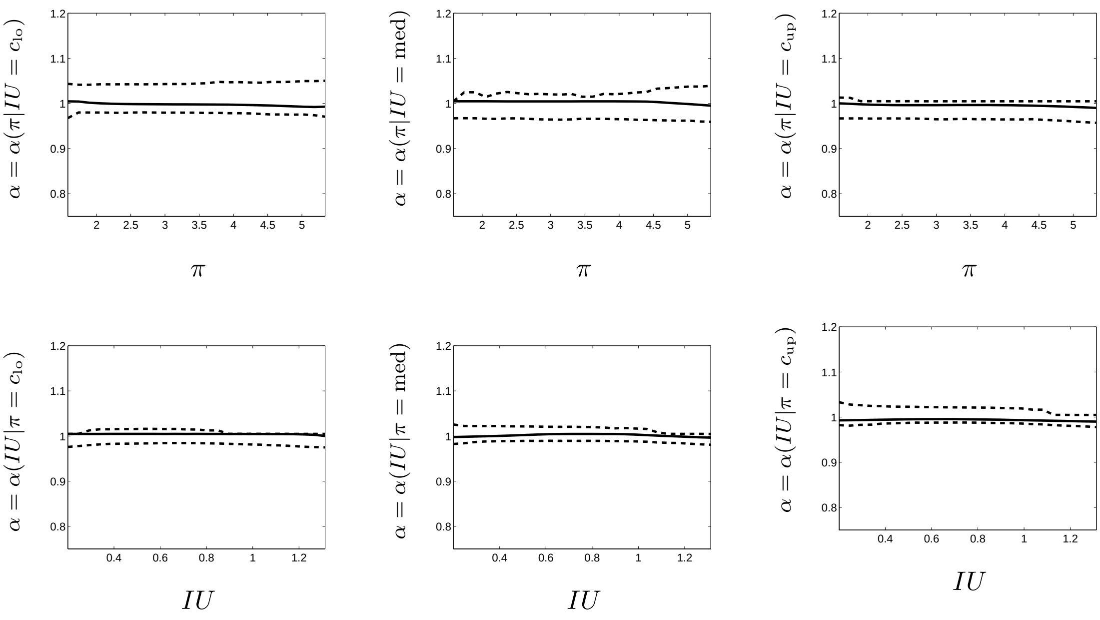
11.2 Functional coefficient estimates of price updating

Fig. 11.1: Functional coefficient estimates for Australia and Belgium

AUSTRALIA

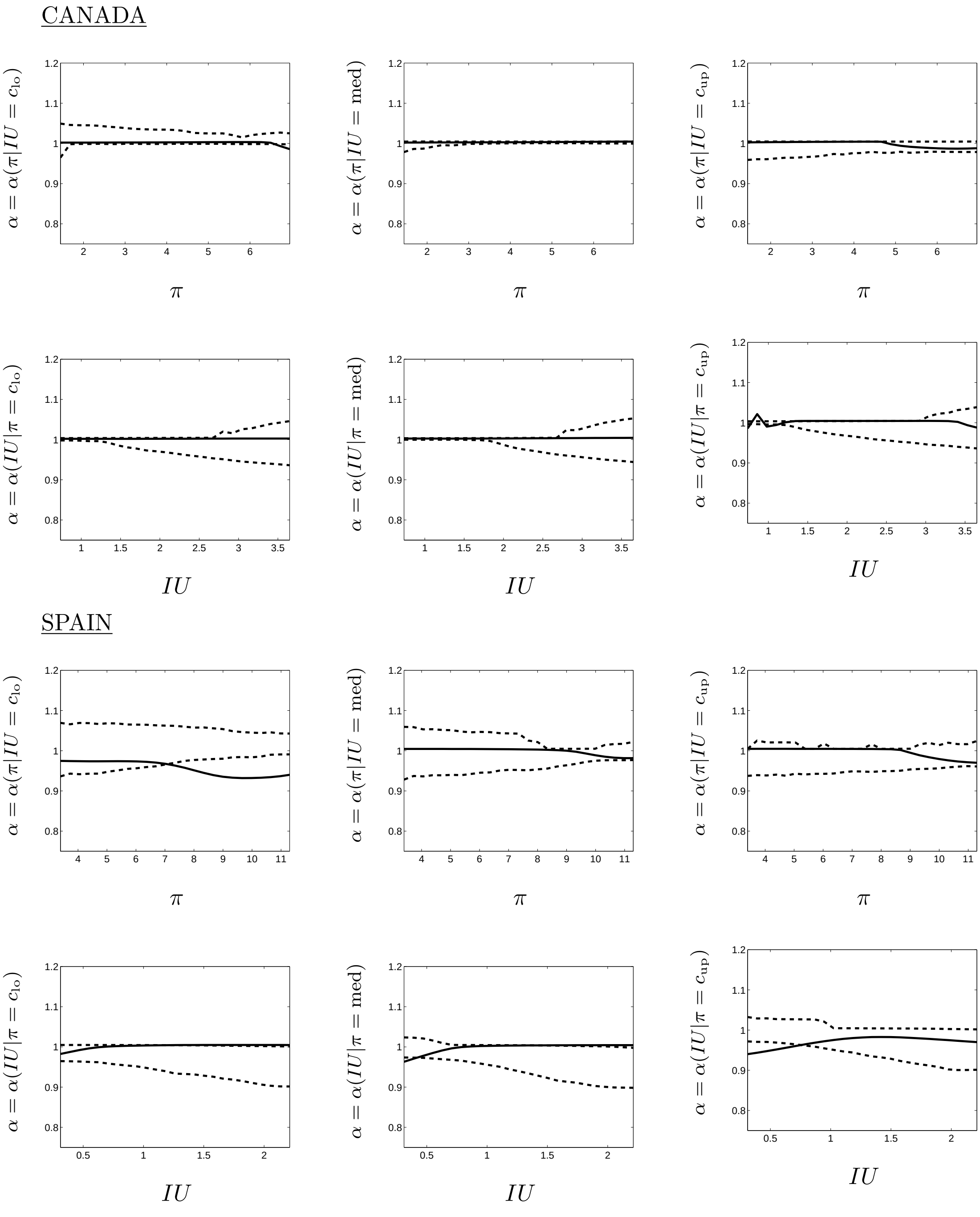


BELGIUM



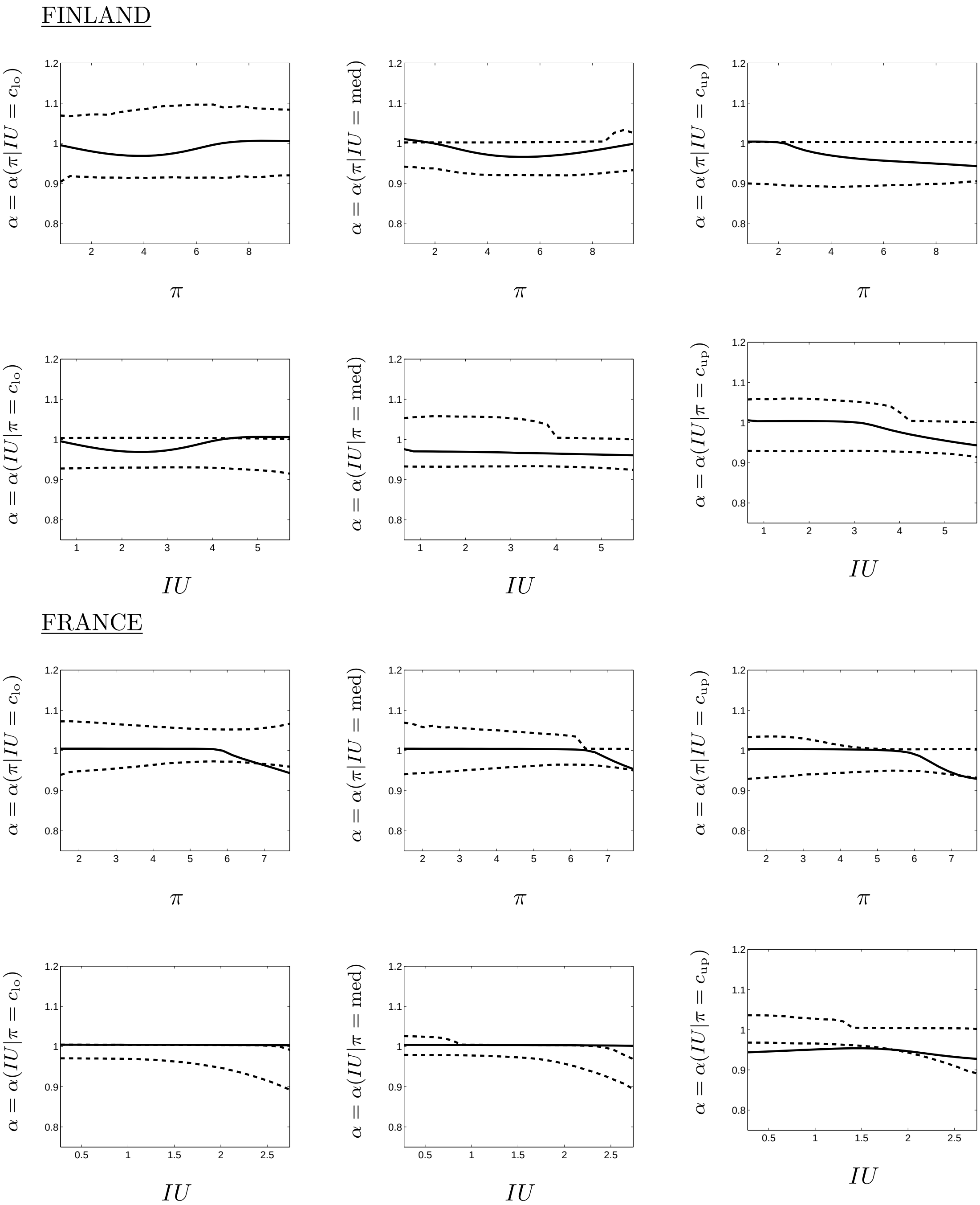
For a description see figure 9.2.

Fig. 11.2: Functional coefficient estimates for Canada and Spain



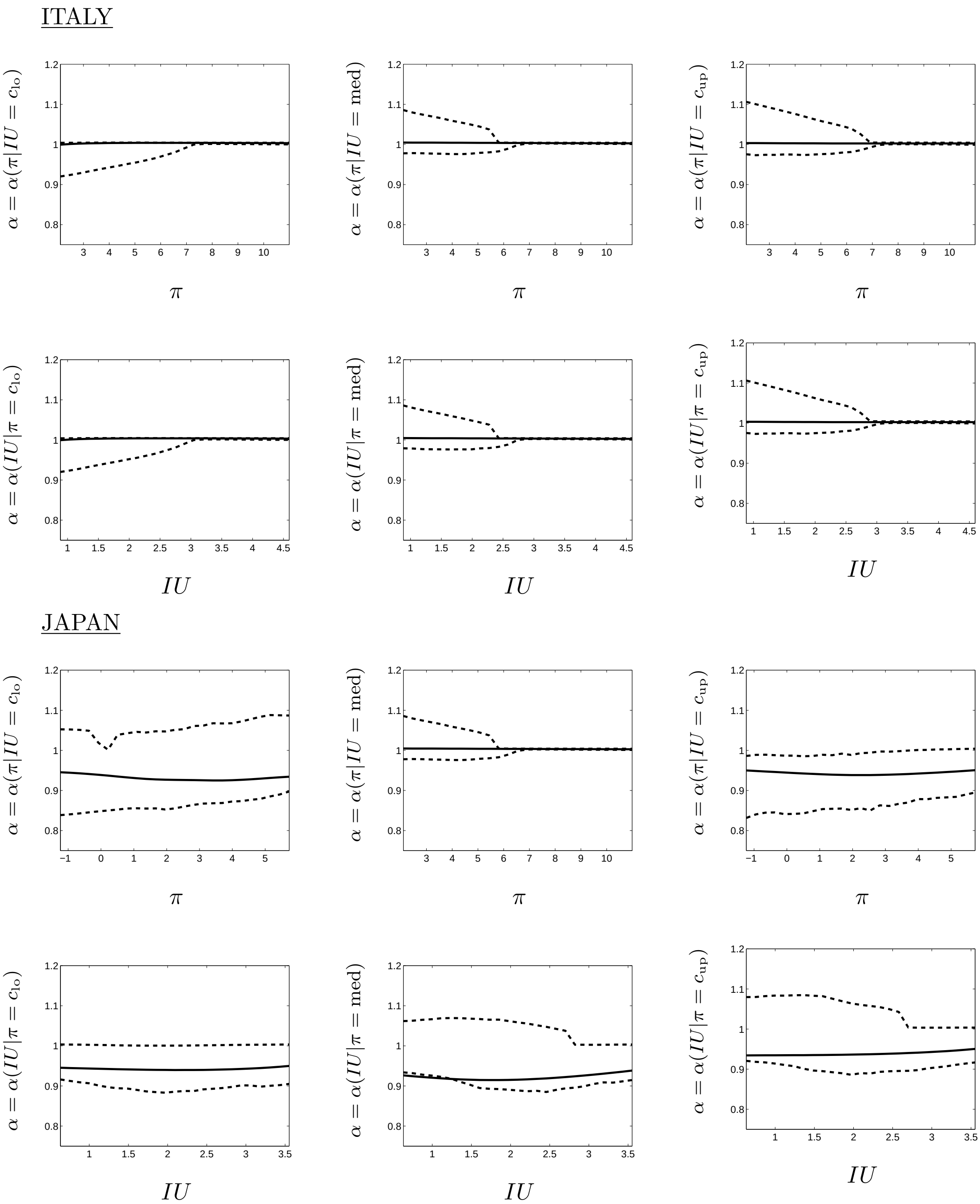
For a description see figure 9.2.

Fig. 11.3: Functional coefficient estimates for Finland and France



For a description see figure 9.2.

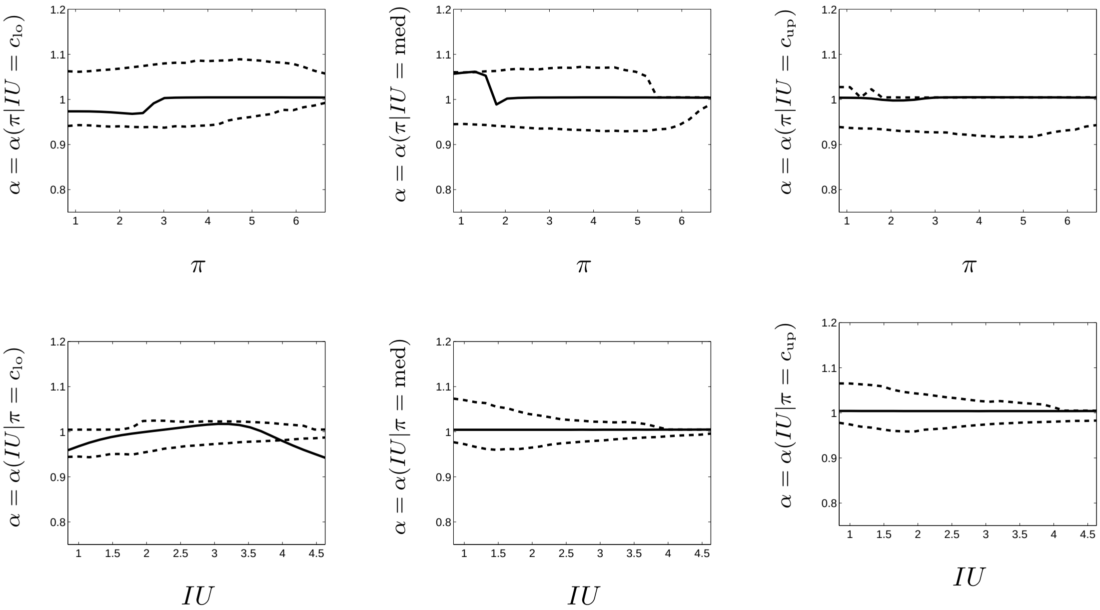
Fig. 11.4: Functional coefficient estimates for Italy and Japan



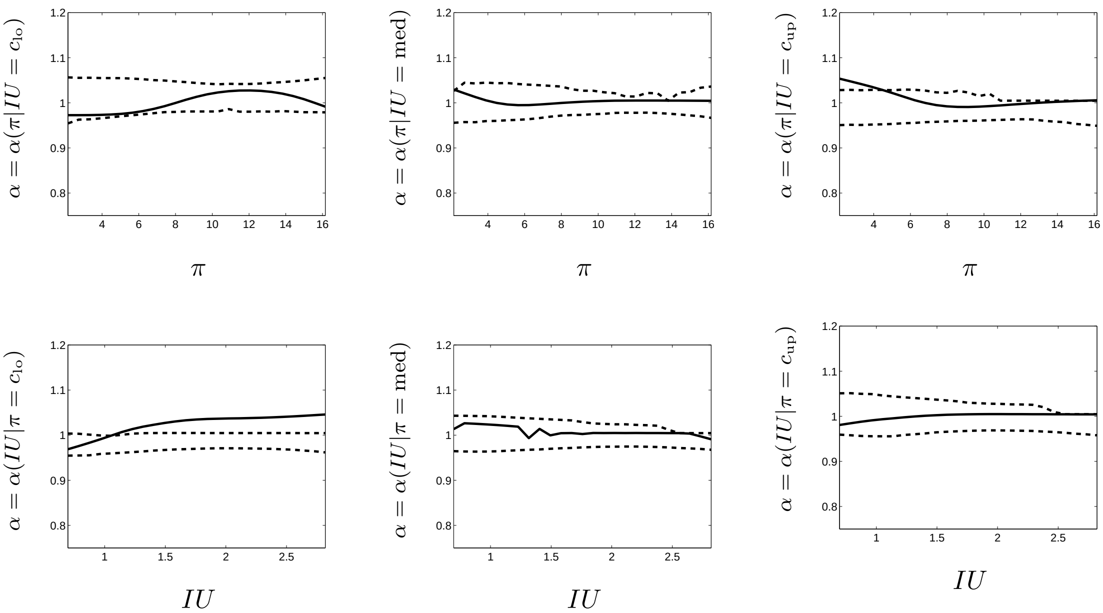
For a description see figure 9.2.

Fig. 11.5: Functional coefficient estimates for the Netherlands and Portugal

NETHERLANDS

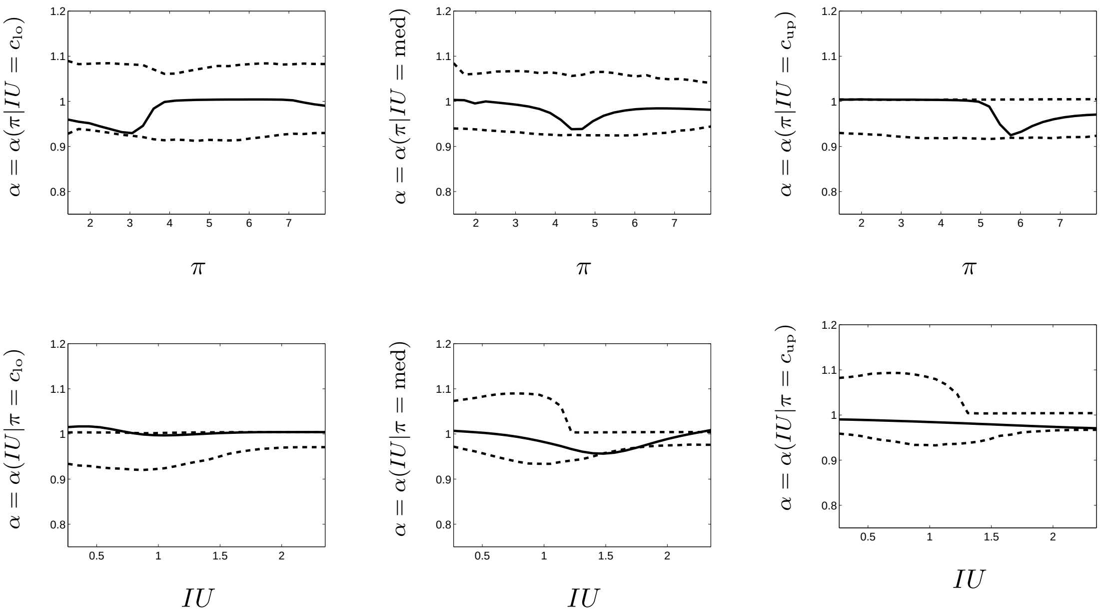


PORTUGAL

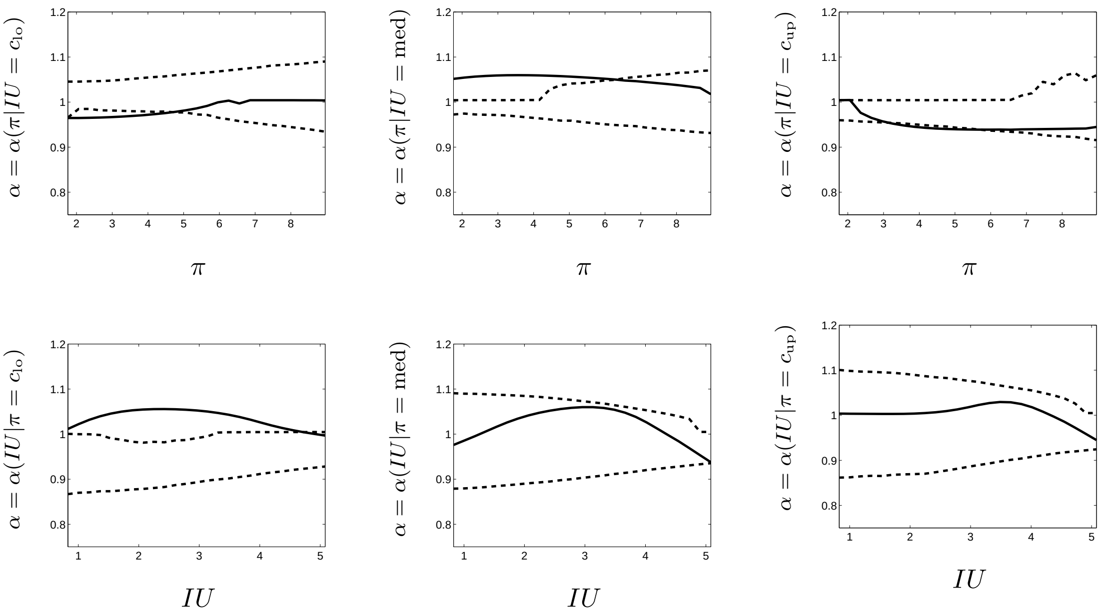


For a description see figure 9.2.

SWEDEN



UK



For a description see figure 9.2.

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Ich erkläre hiermit an Eides Statt, dass ich meine Doktorarbeit "An empirical study on causes and consequences of inflation and inflation uncertainty" selbständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Kiel, Mai 2012

MATTHIAS HARTMANN

Born: 29th January, 1980 in Deggendorf, GERMANY
Postal Address: Knooper Weg 177, 24118 Kiel, GERMANY
Research Assistant, Institute of Statistics and Econometrics, University of Kiel, 24118 Kiel

m.hartmann@stat-econ.uni-kiel.de
www.stat-econ.uni-kiel.de/team/hartmann.shtml

EDUCATION

Institute of Statistics and Econometrics, University of Kiel, Germany
Doctoral studies, 2007-present

University of York, UK
2006-2007, graduated as M.Sc. in Econometrics and Economics

Technical University of Berlin, Germany
2004- 2006, graduated as "Diplom-Volkswirt" (equivalent to M.A. in Economics)

University of Regensburg, Germany
2001-2004, "Vordiplom" (Associate Degree) in Economics

AWARDS AND FELLOWSHIPS

Graduated as M.Sc. Econometrics and Economics with distinction,
University of York, 2007

Teaching and student research fellowship, Deutsche Forschungsgesellschaft,
SFB 649 - Economic Risk, **Humboldt University Berlin**, 2005-2006

5th Nordic Econometric Meeting, **University of Lund**, Sweden (2009), Travel Grant

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FIELDS OF INTEREST

Empirical Macroeconomics, Forecasting, (Applied) Time Series Econometrics

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PUBLICATIONS AND WORKING PAPERS

Hartmann, M., Herwartz, H., 2012. Causal relations between inflation and inflation uncertainty - Cross sectional evidence in favour of the Friedman-Ball hypothesis, **Economics Letters** (115), 144-47.

Hartmann, M., Herwartz, H., Walle, Y., 2012. Where enterprise leads, finance follows. In-sample and out-of-sample evidence on the causal relation between finance and growth, **Economics Bulletin** (32), 871-882.

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REFEREE	**Journal of International Money and Finance, European Journal of Political Economy, Computational Statistics, Economics Bulletin**
CONFERENCE TALKS	**Deutsche Statistische Gesellschaft**, Germany (2009); Nordic Econometric Meeting, **University of Lund**, Sweden (2009); **DIW** Macroeconometric Workshop, Germany (2009); **Deutsche Statistische Gesellschaft**, Germany (2010); **Statistisches Landesamt Schleswig-Holstein**, Germany (2010); **DIW** Macroeconometric Workshop, Germany (2010); Spring meeting of young economists, **University of Groningen**, Netherlands (2011); IWH-INFER Workshop, **IWH Halle**, Germany (2012); **Bundesbank/ifo** Workshop: Uncertainty in Forecasting, Germany (2012, paper accepted)
LANGUAGES	German (native), English (fluent), French (good)
VOLUNTARY	"**Erholungshilfe für Schwerbehinderte e.V.** " (Recreational travels for handicapped persons), Voluntary work subsequent to civil service, Summer 2001; Accounting officer**,** Department of Economics, **University of Kiel**, 2007-2011; Equal opportunities officer, **Institute of Statistics and Econometrics**, 2007-2011

REFERENCES

Prof. Dr. Helmut Herwartz
Chair of Econometrics
Institute of Statistics and Econometrics
24118 Kiel
Tel: +49 431 880 1423
Fax: +49 431 880 7605
email: h.herwartz@stat-econ.uni-kiel.de
Web: www.stat-econ.uni-kiel.de/team/herwartz.shtml

Prof. Dr. Roman Liesenfeld
Chair of Statistics and Empirical Economic Research
Institute of Statistics and Econometrics
24118 Kiel
Tel: +49 431 880 3810
Fax: +49 431 880 7605
email: liesenfeld@stat-econ.uni-kiel.de
Web: www.stat-econ.uni-kiel.de/team/liesenfeld.shtml

Prof. Dr. Uwe Jensen
Institute of Statistics and Econometrics
24118 Kiel
Tel: +49 431 880 1627
Fax: +49 431 880 7605
email: jensen@stat-econ.uni-kiel.de
Web: www.stat-econ.uni-kiel.de/jensen.shtml

Kiel, Mai 2012